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Fair and effective vaccine allocation during pandemics: A system dynamics model for prioritization of socioeconomically vulnerable populations

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ABSTRACT

Health inequality emerged as a central ethical concern during the COVID-19 pandemic. Vaccine prioritization guidelines have been criticized for overlooking socioeconomic disparities, leading to perceived unfairness. This study presents a system dynamics model that integrates age-stratified medical considerations with socioeconomic factors to propose a more equitable vaccine allocation strategy, using England as a case study. The model prioritizes socioeconomically vulnerable groups within the same age cohort until a defined vaccination threshold is reached. Applying an extended Susceptible–Exposed–Infected–Recovered (SEIR) framework and using the Gini coefficient to assess health inequality, the model demonstrates that this approach can simultaneously reduce mortality and improve both input and outcome fairness. Demographic analysis shows that age structure and the size of the susceptible population are critical determinants of threshold-based policy effectiveness. Such policies are less effective in predominantly young populations than in populations with a more balanced age distribution. However, enhancing living conditions for vulnerable groups remains essential to further reducing health inequality. Results also illustrate the pandemic's disproportionate impact on vulnerable groups and emphasize the need for targeted interventions. These findings offer actionable insights for policymakers aiming to enhance fairness and reduce mortality rates in future pandemics.

1. Introduction

The COVID-19 pandemic, caused by SARS-CoV-2, resulted in significant loss of life and suffering since the virus was first identified in December 2019. The World Health Organization (WHO) declared COVID-19 a pandemic in March 2020 since the outbreak rapidly spread to 213 countries and territories worldwide (Lawrence et al., 2022). Excess mortality estimates indicate that the actual number of deaths caused by the pandemic is two to three times higher than the official reported count (Wang et al., 2022; Msemburi et al., 2023). The pandemic also significantly reduced healthcare access and utilization for non-COVID patients, indirectly impacting their health and care needs (Evans et al., 2025; Qi et al., 2025). During the first year of the pandemic, for every 36 to 42 COVID-19-related deaths in England, there was at least one additional non-COVID-19 death among hospital patients (Fetzer et al., 2024).

Implementing public health measures (e.g., national lockdowns, social distancing, and mask mandates) has effectively slowed the spread and reduced COVID-related mortality. For instance, research from Canada indicates that indoor mask mandates led to a 20 to 22% reduction in weekly COVID-19 case growth (Karaivanov et al., 2021). However, the limited scope of the lockdowns and the less stringent restrictions faced by essential workers diminished the full potential of these measures (Di Porto et al., 2022). Studies indicate that a substantial share of mobility reduction during the early stages of the pandemic resulted from voluntary behavioral changes rather than government-imposed restrictions (Cronin and Evans, 2021). Given these complexities, vaccination is recognized as the most effective way to limit transmission and mortality (Hou et al., 2021). The allocation of the initial limited supply of vaccines revealed the ethical challenges associated with implementing a fair allocation system. In fact, it is not just the vaccines themselves that need to be distributed fairly, but the benefits of the vaccination as well (Wu et al., 2020). Thus, the focus on assessing health inequality under pandemic conditions has gained momentum in the health ethics community (Iyanda et al., 2021).

The UK Joint Committee on Vaccination and Immunisation (JCVI) recommended that the first phase of vaccination be administered to individuals at higher risk of severe illness and mortality, prioritizing care home residents, the elderly, health and social care workers, and individuals with comorbidities (DHSC, 2020). Yet, many studies criticize the UK's clinical guidelines as being unfair. In parts of London,

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political, economic, and social dynamics have perpetuated health inequalities during the pandemic among different social groups (Hrynick and Ripoll, 2021). The pandemic has magnified the association between socioeconomic vulnerability and poorer health outcomes (Otu et al., 2020; Cheshmehzangi, 2022; Osama et al., 2021; Kirby, 2020), a pattern that has also been observed in previous pandemics such as the 1918 influenza and the 2009 H1N1 pandemic (Mamelund, 2017; Mamelund and Dimka, 2021a). Mamelund and Dimka (2021b) has also highlighted the critical, often neglected, role of social inequalities in shaping disease outcomes during pandemics and calls for a fundamental shift in preparedness strategies. Similar patterns of disproportionate pandemic impacts on disadvantaged communities have been documented in other countries, including in the United States (Raifman and Raifman, 2020), Brazil (Li et al., 2021), and Spain (Baena-Díez et al., 2020), underscoring that social inequalities in pandemic outcomes are a global concern.

Populations exposed to disproportionate risk are considered vulnerable (Sam, 2020). This includes healthcare and essential workers, the elderly, individuals from lower socioeconomic backgrounds, minority groups, and those with comorbidities, all of whom are particularly susceptible to COVID-19. They experience higher infection rates and mortality due to factors such as living conditions, healthcare access, and socioeconomic status (Bhaskar et al., 2020). Additionally, low-income migrant groups face a significantly higher risk of long COVID than native populations with similar income levels, due to limited resources, barriers to preventive care, and increased exposure (Mkoma et al., 2025). Although existing vaccination frameworks primarily focus on health-related criteria, they often overlook broader social determinants of health (Sekalala et al., 2021). Incorporating socioeconomic factors alongside medical risks for vaccine prioritization is crucial for developing fairer and more effective strategies.

Epidemiological and vaccine allocation models, particularly Susceptible–Infected–Recovered (SIR) type frameworks, which divide the population into disease compartments, have been widely applied to evaluate pandemic interventions. Many have successfully modeled age- and/or comorbidity-based prioritization, providing important insights into reducing mortality (Luebben et al., 2023; Moore et al., 2021; Zhu et al., 2024; Vahdani et al., 2023; Jentsch et al., 2021). However, such approaches often neglect socioeconomic vulnerability, despite long-standing evidence that lower socioeconomic groups experience higher morbidity and mortality in pandemics (Mamelund, 2017). Very few have explicitly integrated socioeconomic vulnerability into dynamic vaccination strategies (Islam et al., 2021; Chen et al., 2021; Stafford et al., 2023), despite clear evidence of its influence on health outcomes. Moreover, no existing work simultaneously combines multiple virus variants, vaccine hesitancy, multi-dose regimens, endogenous behavioral responses, and dynamic pandemic fatigue with quantitative fairness evaluation across population groups for different scenarios and what-if analyses.

To address this gap, we develop an extended SEIR model within a system dynamics framework calibrated for England. The model integrates age-based medical risk with socioeconomic vulnerability, incorporates multiple variants, vaccine hesitancy, multi-dose vaccination, behavioral feedback (risk response and pandemic fatigue), while quantitatively evaluating fairness alongside mortality. This approach combines medical risk factors with socioeconomic vulnerability to assess both fairness and effectiveness in pandemic vaccination. We consider two perspectives of fairness as input (treatment) and outcome (deaths) fairness, which are rarely addressed simultaneously in the existing literature.

England provides an ideal context for this study due to the availability of detailed, high-quality COVID-19 data from the National Health Service (NHS) and other official sources, which allows robust model calibration and validation. Furthermore, conducting the study in the UK enabled direct access to relevant contextual knowledge on vaccination policy and pandemic response, ensuring that the modeling assumptions reflect real-world decision-making processes. While our modeling focuses on England, the framework and insights are relevant to other countries facing comparable challenges. Our research is guided by the question: *How does combining age- and socioeconomic vulnerability-based prioritization affect the fairness and effectiveness of COVID-19 vaccine allocation strategies?*

Our study makes three key contributions. First, we extend traditional age-based medical vulnerability categories by incorporating socioeconomic factors and applying threshold-based sub-prioritization strategies to quantify their impact on both fairness and mortality outcomes. Second, we leverage system dynamics modeling to capture complex, time-dependent behavioral feedback that is difficult to address with conventional analytical approaches. Third, we employ scenario experimentation to extend insights toward future pandemic preparedness.

2. Related literature

This section provides an overview of the current research on epidemiological models, with a focus on compartmental models developed for COVID-19 vaccine prioritization. We analyze the proposed strategies, key model properties, and model outcomes in these studies. Additionally, we explore how fairness considerations are addressed and implemented in vaccine allocation models to set a clear baseline for our model.

2.1. Epidemiological models for vaccine prioritization

The emergence of COVID-19 has increased the focus on epidemiological models, leading researchers to apply various methods such as compartmental models, agent-based models, machine learning, and complex networks (Adiga et al., 2020; Lin et al., 2020; Awasthi et al., 2022; Liu and Lou, 2022; Saadi et al., 2021; Chang et al., 2021). Among these, compartmental models have proven valuable for studying the COVID-19 pandemic trajectory and developing effective vaccine prioritization strategies (Roberto Telles et al., 2021). These models utilize ordinary differential equations to divide the population into compartments based on health status (Zhang et al., 2022). Complex studies often expand the basic SIR model by introducing additional compartments to represent various disease stages or interventions (e.g., SEIR framework including an 'Exposed' state). To account for factors such as age or occupation, populations are stratified into sub-groups, each with its own compartments. This allows modelers to capture heterogeneity in factors influencing disease progression (Gonzalez-Parra et al., 2024).

Previous epidemiological studies on vaccine prioritization have predominantly focused on age-based strategies (Foy et al., 2021; Bubar et al., 2021; Gozzi et al., 2021; Li et al., 2022; Althobaity et al., 2022; Penn and Donnelly, 2023; Zavrakli et al., 2023; Angelov et al., 2023; Galli et al., 2023; Lyu et al., 2024; Jentsch et al., 2021; Rahmandad, 2022; Vahdani et al., 2023; Zhu et al., 2024). These studies present conflicting results regarding the effectiveness of different age-based vaccination strategies. Some have expanded the medical risk perspective by including individuals with comorbidities (Luebben et al., 2023; Moore et al., 2021). Additionally, several studies have explored prioritizing healthcare workers (Moore et al., 2021; Ko et al., 2021; Zhang et al., 2024; MacIntyre et al., 2022) and essential workers (Buckner et al., 2021; Ferranna et al., 2021) due to their higher risk of infection based on their occupation. Other research has examined location-based prioritization policies rather than focusing on individual-level factors (Ghazal et al., 2022; Cao et al., 2022; Erdoğan et al., 2024). Only a few studies in the literature have emphasized the importance of considering social and economic factors such as ethnicity, income levels, living conditions, and race when determining priority groups (Islam et al., 2021; Kadelka et al., 2022; Chen et al., 2022; Stafford et al., 2023).

The COVID-19 vaccine roll-out co-occurred with the emergence of SARS-CoV-2 variants with varying infectivity, severity, and mortality (Campbell et al., 2021). To effectively analyze the impact of vaccination on disease dynamics, models need to incorporate variants (Gonzalez-Parra et al., 2024). However, limited research has addressed multiple variants in their models. For instance, Hou and Bidkhori (2024) used time-varying infection probabilities to address the impact of multiple virus variants. Their SEIR model evaluated vaccine prioritization strategies tailored to heterogeneity in health conditions and social activity levels across population groups. Similarly, Luebben et al. (2023) explored the effects of variants by averaging infection probabilities for each sub-population based on the prevalent variants. They concluded that prioritizing high-transmission groups is optimal when transmission is low, whereas vaccinating high-fatality groups yields greater mortality reduction when transmission levels are high.

Despite the availability of highly effective COVID-19 vaccines, a significant portion of the population refuses vaccination (Gonzalez-Parra et al., 2024). Vaccine hesitancy poses a serious threat to the global roll-out of vaccines (Althobaity et al., 2022). Some studies have modeled vaccine hesitancy as a constant factor across the entire population. Moore et al. (2021) assumed a 70% vaccine uptake across all age groups in their SEIR-V (V: vaccinated) model, which differentiates between detected and undetected cases. Similarly, Foy et al. (2021) used an age-structured SEIAQR-V (A: asymptomatic, Q: quarantined) model, assuming 75% coverage for each age group. Both studies suggested prioritizing the elderly to minimize deaths. Bubar et al. (2021) used a maximum of 70% vaccination coverage for any age group in their model and highlighted that prioritizing adults aged 20–49 lowers both infections and mortality.

Vaccine hesitancy varies widely by country, and more notably by age and socioeconomic status. To address this, some studies have incorporated different levels of vaccine hesitancy across different priority groups (Galli et al., 2023; Zavrakli et al., 2023). Chen et al. (2022) considered varying levels of vaccine hesitancy across different communities based on age, occupation, income, and race. Their study found that prioritizing the most disadvantaged communities in each demographic group can lower mortality. However, high vaccine hesitancy in low-income communities reduces these benefits. Galli et al. (2023) used an age-stratified SIR model to analyze different vaccination coverage levels for individuals aged 30–49. Prioritizing those aged 50 and older reduced critical cases more effectively than random vaccine allocation.

Some of the most effective COVID-19 vaccines, such as Pfizer-BioNTech, Moderna, and AstraZeneca, require a two-dose regimen for optimal protection (Gonzalez-Parra et al., 2024). While a single dose provides partial immunity, the second dose significantly boosts protection (McMenamin et al., 2022). Some models account for different vaccine effectiveness and timing between doses in vaccination strategies. Zhu et al. (2024) developed an age-stratified two-dose model that covers multiple infection stages (e.g., asymptomatic, presymptomatic, symptomatic, severely symptomatic, hospitalized). Their findings showed that prioritizing the elderly reduces deaths, while their sensitivity analysis shows that first-dose efficacy may impact vaccine prioritization. Vahdani et al. (2023) highlighted the need to vaccinate high-risk individuals and those in high-contact areas, using a two-dose model that distinguishes between quarantined and non-quarantined infected individuals. Erdoğan et al. (2024) proposed a multi-dose model to minimize mortality by optimizing vaccine allocation. Their approach focuses on multi-period dose distribution across regions with an extended SIR framework including hospitalized patients.

The impact of human behavior on COVID-19 spread highlighted the need to integrate human responses with disease dynamics in simulations (Gentili and Cristea, 2020). Some models employed simplistic time-based approaches, such as adjusting contact patterns to reflect lockdowns (see Lyu et al., 2024; Moore et al., 2021; Ko et al., 2021; Zhu et al., 2024) or assuming a return to pre-pandemic contact levels post-vaccination (see Bubar et al., 2021; Gozzi et al., 2021; Althobaity et al., 2022). While these models fit historical data well, they often lack reliability for long-term policy analysis (Rahmandad et al., 2022).

To address these limitations, some researchers adapted human responses according to the system's state. Rahmandad (2022) enhanced the SEIR model with an endogenous feedback loop for behavioral responses to adjust social distancing levels based on reported deaths. Similarly, Suphanchaimat et al. (2021) and Jentsch et al. (2021) developed SEIR models that included detailed infection states (e.g., presymptomatic, asymptomatic, symptomatic) and modified social contacts based on active cases. These models improved the understanding of the pandemic's trajectory and shifted the optimal vaccination strategies towards prioritizing high-contact groups to reduce mortality. Additionally, Islam et al. (2021) and Kadelka et al. (2022) included the impact of active cases on social contacts in their comprehensive SEIR model with detailed stages of infection, hospitalization, and vaccination status. Islam et al. (2021) segmented the population by age, comorbidity, job, and living conditions. They discovered that prioritizing the working-age group led to fewer infections but higher mortality. Kadelka et al. (2022), on the other hand, created priority groups based on age and ethnicity. Their research concluded that incorporating ethnicity into vaccine prioritization could help reduce COVID-19 deaths. In addition to these epidemiological modeling approaches, some studies have integrated SD with optimization and artificial intelligence to design and manage vaccine supply chain networks under pandemic conditions. For example, Kamran et al. (2023) developed a hybrid SD–AI framework to support vaccine distribution planning under uncertain supply and demand.

2.2. Fairness considerations in vaccine prioritization

Vaccine prioritization requires both rational and ethical considerations to address inequities and disparities among populations (Bubar et al., 2021). Health equity is achieved when everyone can attain their full potential for health and well-being, without unfair, avoidable, or remediable differences among groups of people (WHO, 2025). While fairness and equity are different concepts, they are often used interchangeably. Ensuring fairness becomes more challenging in collective decision-making (Griffin, 1985), particularly in global crises such as the pandemic. The quantitative assessment of fairness in vaccine allocation resulting from prioritization models remains limited. This section categorizes fairness considerations in vaccine prioritization studies into three groups: (1) studies analyzing model outcomes from a fairness perspective without quantitative assessments of fairness; (2) studies providing quantitative evaluations and comparisons of fairness; and (3) studies recognizing fairness as a future research area or limitation.

2.2.1. Qualitative evaluations of model outcomes from a fairness perspective

Some studies, while not measuring fairness quantitatively, have interpreted model outcomes from a fairness perspective. For instance, Buckner et al. (2021) concentrated on minimizing deaths to benefit fairness by promoting the common good and maximizing benefits. Their focus on essential workers demonstrates how ethical values, such as prioritizing those at risk, can align with efforts to reduce mortality. Similarly, Kadelka et al. (2022) addressed the ethical advantages of ethnicity-based differentiation in prioritization strategies. However, their work is not based on direct (quantitative) comparisons and detailed analyses of model outcomes in terms of fairness. Ferranna et al. (2021) argued that vaccination strategies should assign greater weight to essential workers from a social justice standpoint.

2.2.2. Quantitative evaluations of model outcomes from a fairness perspective

Studies that quantitatively measure equity to address fairness fall into two categories: input and outcome equity (Gutjahr, 2023). Input equity ensures all sociodemographic groups receive the same treatment

(e.g., vaccines) (Pressman et al., 2021). For example, Erdoğan et al. (2024) incorporated equity constraints in their optimization model to minimize discrepancies across locations. They used the decision variable of a minimum vaccination percentage for each site to evaluate input equity. Similarly, Vahdani et al. (2023) examined fairness in vaccine distribution among different regions. They used the minimum delivery-to-demand ratio as a measure of input equity in their analysis. While fair vaccine distribution enhances social satisfaction, it may not always effectively halt pandemics. Thus, they concluded that a trade-off exists between ensuring fair access and controlling the pandemic in high-risk areas. Building on this line of research, Ghasemi et al. (2025) proposed an optimization-based testing kit allocation framework that integrates efficiency and fairness objectives under supply constraints, illustrating how quantitative modeling can address both epidemiological and ethical priorities.

Outcome equity refers to achieving the same patient outcomes across all sociodemographic groups. In this context, the primary goal of vaccination is to reduce deaths (Pressman et al., 2021). One simple approach to assessing outcome equity is by comparing the distribution of deaths. For instance, Islam et al. (2021) examined how deaths were distributed across different age groups and used the Shannon entropy to summarize the variation in mortality as a single measure of health equity. Although their model accounted for various priority groups apart from age (e.g., comorbidity status, occupation type, and living conditions), the study focused only on age-equitable vaccine allocation. Notably, the prioritization strategy that minimizes overall mortality leads to a more equitable distribution of fatalities across age groups. However, the most age-equitable allocation strategy performed poorly regarding other objectives.

Given the disproportionate impact of COVID-19 on marginalized communities, Stafford et al. (2023) used an age-and-race-stratified extended SEIR model to analyze vaccine distribution among two racial groups. The study aimed to determine optimal vaccine allocation while minimizing mortality and addressing inequity. To assess disparities in mortality, the authors introduced several metrics: relative disparity, absolute disparity, and the index of disparity. Relative disparity quantifies how much the mortality rate ratios between the two racial groups deviate from perfect equity (defined as a ratio of 1). Absolute disparity, on the other hand, measures the differences in mortality rates by race. The index of disparity assesses how much the mortality rate for each racial group diverges from the mean mortality rate. The findings revealed a significant trade-off between reducing disease burden and improving equity, especially with limited vaccine supply (e.g., 10% coverage). However, as vaccine availability increased, it became feasible to optimize both mortality reduction and equity simultaneously.

Chen et al. (2022) developed an SEIR model that considers demographic and mobility differences among communities based on social utility and health equity. They measured social utility by the reduction in total mortality and defined health inequities as disparities that could be alleviated through vaccination, regardless of whether these disparities arise from pre-existing health conditions or social deprivation. Their analysis explored four dimensions of equity: age, income, occupation, and race/ethnicity. To quantify disparities in fatality rates, they utilized the Gini coefficient which is a well-established tool for measuring income inequality in economics. By examining the negative values of the Gini coefficient for each dimension, the researchers assessed levels of inequity across various strategies. Prioritizing the most disadvantaged communities not only significantly enhances equity but also improves social utility. This approach underscores the importance of targeted vaccination efforts to address disparities.

2.2.3. Fairness as a research area

Several authors recognized the need to address fairness as a critical research area for future pandemic preparedness. Foy et al. (2021) emphasized the success of rapid vaccine development and approval process but noted that ongoing challenges in ensuring fair distribution need to be addressed. Bubar et al. (2021) called for more equitable vaccine prioritization models to mitigate disparities in healthcare access, particularly for disadvantaged populations. Zhang et al. (2024) and Galli et al. (2023) highlighted the need for policies that address global health inequities. They specifically pointed out the importance of preventing high-income regions from monopolizing resources and alleviating the burden of COVID-19 in low-income countries.

2.3. Summary and literature gap

Table 1 provides a comparative analysis of the literature based on key characteristics (priority groups, consideration of multiple variants, vaccine hesitancy, multi-dose vaccine, endogenous risk response, pandemic fatigue, and fairness). In vaccine prioritization literature, the socioeconomically vulnerable groups that are disproportionately affected by the COVID-19 pandemic are only considered sparsely. Additionally, there is a lack of studies that integrate these characteristics while interpreting outcomes from both fairness and mortality perspectives. Fairness is also typically examined from a single perspective, either input or outcome. Although Islam et al. (2021), Chen et al. (2021), and Stafford et al. (2023) provide quantitative evaluations of fairness while incorporating socioeconomically vulnerable groups in their vaccine prioritization models, they differ from our study in several ways. All three focused on short timelines for the US population, and thus did not examine pre-vaccine pandemic dynamics. They excluded multiple variants, pandemic fatigue, and pandemic learning effects. All assumed a single-dose vaccine and did not account for loss of natural or vaccine-induced immunity. Behavioral responses are limited: Islam et al. (2021) included endogenous risk responses, whereas Chen et al. (2021) and Stafford et al. (2023) did not, meaning increases in mortality do not influence human behavior. Regarding vaccine effectiveness, Islam et al. (2021) considered protection only against infection, Chen et al. (2021) assumed full protection against infection and death, and Stafford et al. (2023) included effects on infection, hospitalization, and death.

To contribute to these issues, we develop an extended SEIR model for England, covering a longer timeline of 600 days, which captures approximately the first half of the pandemic and includes both pre- and post-vaccine dynamics. The model incorporates socioeconomic vulnerability groups, multi-dose vaccination, and vaccine hesitancy, while explicitly modeling behavioral aspects such as endogenous risk response, pandemic fatigue, and pandemic learning. We evaluate fairness from both input and outcome perspectives. Furthermore, we model vaccine effectiveness across transmission, infection, and death, using empirically grounded values from the literature. We also introduce a threshold-based sub-prioritization strategy to quantify its effects on both fairness dimensions and overall mortality for managing and preparing for future pandemics.

3. Methodology

System Dynamics (SD) modeling employs stock variables to partition the population into compartments and is widely used in epidemiological modeling. It focuses on capturing feedback loops, time delays, and nonlinear interactions (Forrester, 1994), and is particularly valuable in healthcare for modeling the interplay between disease transmission, resources, and human behavior (Sterman, 2006). We develop an SD model within an extended SEIR compartmental framework that stratifies the England population by medical vulnerability, socioeconomic vulnerability, vaccination status, and vaccine hesitancy.

The medical vulnerability is addressed by dividing the population into age-based subgroups, as age is an important correlate of COVID-19 susceptibility (Goldstein et al., 2021; Davies et al., 2020), severity (Mueller et al., 2020), and mortality (Levin et al., 2020). In this study, socioeconomic vulnerability is defined as exposure to

Table 1
Summary of COVID-19 vaccine prioritization studies.

Study	Priority groups[a]	Multiple variants	Vaccine hesitancy	Multi-dose vaccine	Endogenous risk response	Pandemic fatigue	Fairness
Cartocci et al. (2021)	A						
Bubar et al. (2021)	A		✓				
Gozzi et al. (2021)	A		✓				
Jentsch et al. (2021)	A		✓		✓		
Foy et al. (2021)	A		✓				
Althobaity et al. (2022)	A		✓				
Rahmandad (2022)	A		✓		✓	✓	
Li et al. (2022)	A		✓				
Penn and Donnelly (2023)	A						
Zavrakli et al. (2023)	A		✓				
Angelov et al. (2023)	A						
Galli et al. (2023)	A		✓				
Vahdani et al. (2023)	A			✓			Input
Lyu et al. (2024)	A						
Zhu et al. (2024)	A		✓	✓			
Luebben et al. (2023)	A, C	✓	✓				
Moore et al. (2021)	A, C, HW		✓				
Islam et al. (2021)	A, C, O, LC	✓	✓		✓		Outcome
Buckner et al. (2021)	A, EW						
Ferranna et al. (2021)	A, EW						Outcome
Ko et al. (2021)	A, HW						
MacIntyre et al. (2022)	A, HW			✓			
Zhang et al. (2024)	A, HW						
Kadelka et al. (2022)	A, O, EG	✓	✓		✓		
Chen et al. (2022)	A, O, I, EG		✓				Outcome
Stafford et al. (2023)	A, EG						Outcome
Hou and Bidkhori (2024)	HR, HC	✓					
Suphanchaimat et al. (2021)	MG				✓		
Ghazal et al. (2022)	L						
Cao et al. (2022)	L		✓				
Erdoğan et al. (2024)	L			✓			Input
Our study	A, SVG	✓	✓	✓	✓	✓	Both

[a] A: age, C: comorbidity, HW: health workers, O: occupation, LC: living condition, EW: essential workers, EG: ethnic groups, I: income, HR: high risk, HC: high contact, MG: migrant groups, L: location SVG: socioeconomic vulnerability groups.

multiple forms of deprivation, including income, employment, education, health, crime, barriers to housing and services, and the living environment. To capture this vulnerability, we use the Index of Multiple Deprivation (IMD), which combines these factors into a single composite measure for England (MHCLG, 2019a). Each age group is further stratified into two subgroups based on IMD quintiles. Vaccination status monitors unvaccinated and vaccinated populations, estimates vaccine demand, and accounts for vaccine-induced immunity. We differentiate between first and second doses, as they provide different levels of protection against infections and deaths (McMenamin et al., 2022). Finally, vaccine hesitancy is incorporated to capture behavioral differences in vaccine uptake.

3.1. Stock and flow diagram

The stock and flow diagram incorporates separate SEIR structures for both vaccinated and unvaccinated individuals and distinguishes between first- and second-dose vaccinations. This allows us to define interacting vaccination subpopulations: unvaccinated (NoV), first-dose recipients (V1), and fully vaccinated individuals (V2). The model ensures individuals are completing their first dose before receiving the second. We define three age groups: young (20–54), middle-aged (55–74), and elderly (75+), based on the differences in their mortality rates according to the official data in England (ONS, 2023a). There is a significant difference in the age-standardized COVID-19 mortality rates between the two most deprived deciles of the IMD and the rest (Welsh et al., 2022). Using this difference, we classify the most deprived quintile as "vulnerable" and the remaining as "non-vulnerable".

Each population subgroup is divided into vaccine-positive and vaccine-hesitant individuals, with vaccination flows restricted to the vaccine-positive group. This fixed hesitancy approach is based on empirical data (ONS, 2021b) indicating stable hesitancy levels over the simulation period, during which vaccine uptake was primarily constrained by supply. Considering the vaccination status (NoV, V1, V2), age (Young, Mid, Old), vulnerability status (vulnerable, non-vulnerable), and vaccine hesitancy (Positive, Hesitant), our model includes 36 interacting population groups. We utilize the subscript functionality of Vensim DSS version 9.3.0 (Ventana Systems, Inc.) to model the subpopulations.

Infection modeling

We cover the first 600 days of the COVID-19 outbreak in England, starting from the report of the first case on January 30, 2020 (Lillie et al., 2020). This period captures the resource-constrained phase of the vaccination rollout, during which all population groups became eligible for two doses before booster campaigns began, and prioritization choices were most critical. At the start of the simulation, everybody is in the $\text{Susceptible}_{\text{NoV}}$ stock, except a few who are initially infected and/or exposed. While some individuals had partial immunity to early SARS-CoV-2 variants due to prior exposure to other coronaviruses (Grifoni et al., 2020), our model does not explicitly represent such individual heterogeneity. Instead, these effects are incorporated into aggregate parameters through calibration to observed data.

The model includes the Alpha and Delta variants to address variant-specific parameters such as infection fatality rate, incubation period, and number of infectious contacts. The Omicron variant is excluded, as it occurred after the defined period of the model. Nonetheless, our results are expected to be robust for three main reasons. First, medical vulnerability remains age-dependent across variants (Levin et al., 2020). Second, structural drivers of exposure risk in socioeconomically vulnerable groups persist (Beale et al., 2022). Third, our analysis focuses on relative rather than absolute comparisons of deaths and fairness because relative measures provide a normalized basis for comparing groups, independent of absolute scale, which is critical when evaluating equity in vaccine allocation. While a future pathogen with

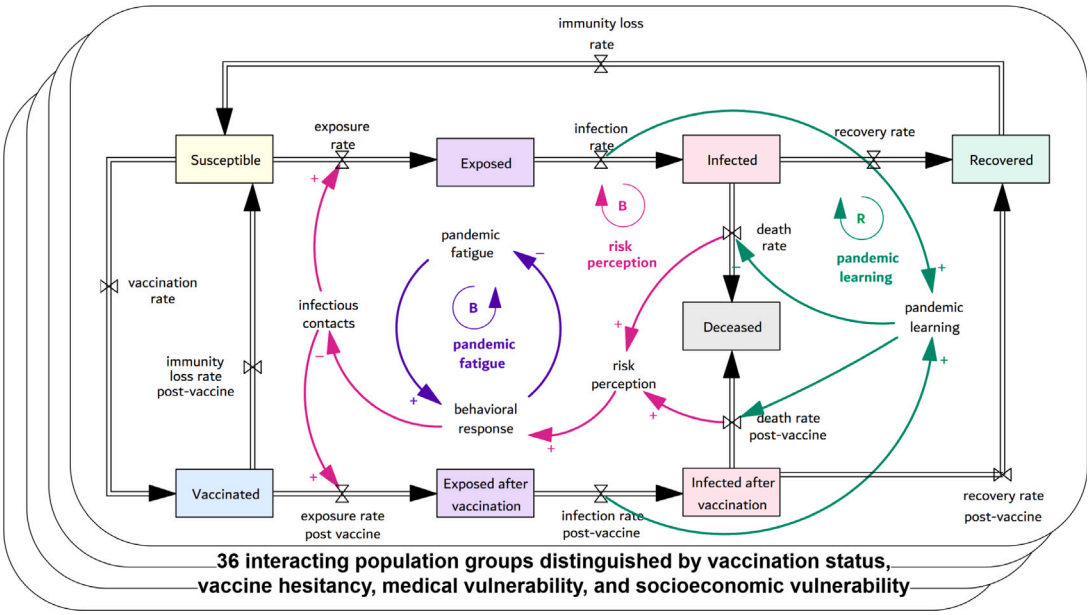

Fig. 1. Simplified stock and flow diagram.

substantially different risk profiles (e.g., such as higher severity among younger groups) would require revisiting these assumptions, within the known dynamics of COVID-19, our conclusions remain valid and generalizable. Fig. 1 presents a simplified stock-and-flow diagram of the model (see the Supplementary file for the complete version). Each stock represents multiple parallel structures corresponding to different age groups, vaccination statuses, vaccine hesitancy levels, and socioeconomic vulnerability categories. In total, 36 parallel SEIR structures are simulated, with interactions occurring across all groups. Parameter indices are detailed in the Parameter Estimation and Model Validation section.

The main driver of infectious disease outbreaks is the "infection reinforcing loop" which generates the initial exponential growth in the number of cases. As the number of infected individuals increases, their infectious contacts (Ci) further raise the exposure rate. Ci is the product of the contact rate and virus infectivity (Rahmandad, 2022) and can have different values based on the age group, socioeconomic (SE) vulnerability, and variant type (Gimma et al., 2022; Beale et al., 2022; Campbell et al., 2021). Eq. (1) provides a formula for Ci for different age and SE vulnerability levels.

$$\begin{aligned} Ci_{Age,\,SE} = & reference\ Ci \times age\ multiplier\ Ci_{Age} \times \\ & vulnerability\ multiplier_{SE} \times \\ & variant\ impact\ Ci \times behavioral\ response_{Age} \end{aligned} \tag{1}$$

We estimate the value of Ci by calibrating the model for the young and non-vulnerable population, and then use this as a reference to calculate Ci values for other age groups and SE vulnerability levels. Age-related variations are integrated into the model using age multipliers based on a social contact survey during the pandemic in England (Gimma et al., 2022). Similarly, the vulnerability multipliers, which apply the variations in Ci for vulnerable groups, are derived from a study on the exposure to public activities during the pandemic (Beale et al., 2022). The effect of variants on Ci is a time-dependent variable which gradually changes based on the infectivity in the dominant variant (UKHSA, 2021). Finally, using the behavioral response factor, we apply the impact of the endogenous societal risk-response on Ci. Shifts in risk perception lead to changes in contact rates (Rahmandad, 2022). This feedback mechanism serves as a balancing loop to counteract the spread of infection.

We formulate the behavioral response factor as a function of perceived risk and responsiveness, following Lim et al. (2023). They acknowledged that the time required to respond to increasing risks may differ from the time to respond to decreasing risks. Similarly, we allow an asymmetric adjustment time for increasing vs. reducing perceived risk. Responsiveness reflects the age-specific collective reactions of society to risks within a community. Its value is a smoothed version of the initial responsiveness, adjusted by the pandemic fatigue multiplier for each age group. Additionally, we model the increased societal pressure on contact patterns during national lockdowns using a multiplier which becomes active during these periods. The formulation of the *response* variable in our model is presented in Eq. (2).

$$behavioural\ response_{Age} = \frac{lockdown\ multiplier}{1 + responsiveness_{Age} \times risk\ perception_{Age}} \tag{2}$$

Pandemic fatigue, or adherence fatigue, as stated by Rahmandad et al. (2021), refers to the decreased motivation to follow social distancing measures and adopt health-protective behaviors (Tang et al., 2021). Public health experts expressed concerns that pandemic fatigue could threaten global health (Cabrera, 2021). In our model, prolonged pressure on social contacts in recent months increases the pandemic fatigue multiplier (Rahmandad and Sterman, 2022). In turn, the multiplier decreases the responsiveness and thus the behavioral response, leading to higher contact rates (pandemic fatigue loop). These changes vary across age groups as pandemic fatigue is less common among the elderly (Leung et al., 2022).

We consider an incubation period between exposure and infection. Following infection, the infection fatality rate (IFR) determines the rates of death and recovery. The IFR varies by age, SE vulnerability, and variant type (Levin et al., 2020; Ahmad et al., 2022). Similar to Ci, the effect of variants on IFR is time-dependent and gradually changes with the dominant variant (UKHSA, 2021). Additionally, COVID-19 patient care has improved over time through better treatments and protective protocols (Mozaffari et al., 2025; Akinosoglou et al., 2023). We capture these improvements using a standard learning curve (pandemic learning) in which IFR decreases as clinicians gain experience from cumulative cases (Rahmandad and Sterman, 2022). Finally, recovered individuals return to the susceptible population after losing immunity (Dan et al., 2021), making reinfections possible.

$$\begin{aligned} IFR_{Age,SE} = & reference\ IFR \times \\ & age\ multiplier\ IFR_{Age} \times vulnerability\ multiplier\ IFR_{SE} \times \\ & variant\ impact\ IFR \times pandemic\ learning \end{aligned}$$

(3)

Vaccination modeling

Vaccine administration begins at time $t = 314$, corresponding to the start of the vaccination campaign in England (NHS England, 2020). Our model focuses on two-dose mRNA vaccines, which are among the most effective and widely administered options (Gonzalez-Parra et al., 2024). Vaccinated individuals are still considered potentially susceptible, meaning they can become infected, but both their Ci and IFR are reduced compared to unvaccinated individuals. Protection is dose-dependent: the first dose provides partial immunity, while the second dose confers stronger and sustained protection throughout the simulation. This sustained protection is based on the assumption that the earliest immunity loss, according to a six-month duration of immunity (Doria-Rose et al., 2021), occurs close to the end of the simulation horizon at $t = 550$. If a fully vaccinated individual becomes infected and subsequently loses immunity during recovery, they return to the susceptible population and are no longer considered vaccinated. In our model, vaccine effectiveness varies by dose and variant type, representing an important balancing feedback loop that reduces both infection and fatality among vaccinated individuals.

Risk compensation suggests that vaccinated individuals might feel safer and take more risks, potentially increasing disease transmission. Evidence from the UK shows that individual vaccination status does not alter personal behavior. Instead, higher regional vaccination coverage is associated with increased social contacts, suggesting that risk compensation primarily emerges at the population level as collective immunity rises (Buckell et al., 2023). Our estimates of the critical immunization threshold (q_c) across R_0 values (Elsaid et al., 2021) and vaccine effectiveness show that q_c is reached only after epidemic peaks. Consequently, behavioral relaxation from surpassing q_c is unlikely to affect key epidemic outcomes.

We do not account for hesitancy between doses, assuming that all individuals who receive the first dose will request the second dose. This simplification is supported by the close agreement between model outputs and observed NHS England (2025) data for both first- and second-dose coverage during the simulation period (see the Parameter Estimation and Model Validation section). Thus, dose-to-dose hesitancy has a negligible impact within our simulation timeframe.

The infection model is expanded to accommodate the vaccination rate which depends on two key variables: eligibility for vaccination and nominal vaccination rate. To consider the impact of fair vaccine distribution, we link the eligibility for vaccination to a threshold, so the non-vulnerable groups become eligible to receive their first doses only after the percentage of vaccinated vulnerable individuals in the same age group reaches that threshold. In the base run, the prioritization of the vulnerable groups is not considered, so the threshold value is set to zero. This means both vulnerable and non-vulnerable groups in the same age cohort become eligible simultaneously. The administration of the second dose will follow the prioritization approach in the first dose, but with a predefined time gap. The *nominal vaccination rate* determines the number of eligible susceptible individuals within each vaccine-positive sociodemographic group. If this rate exceeds the daily vaccination capacity, a proportion of eligible groups (based on their size) gets vaccinated. The full list of the model formulation is provided in the Supplementary file. Below, we provide a summary of assumptions:

- The model focuses on two-dose mRNA vaccines and does not consider third doses.
- There is no loss of immunity after the second dose.
- Daily vaccine capacities for age groups equal the amounts of daily administered doses.
- The leftover vaccine from the previous day (if any) cannot be used the next day.
- All individuals who received the first dose are assumed to request the second dose.
- Vaccine hesitancy varies among subgroups but stays constant during the simulation.
- The model does not account for births, immigration, and non-COVID-19 deaths.
- The model includes only individuals aged 20 and over.
- Testing and hospitalization are excluded for simplicity.
- Vaccine demand comes only from susceptible individuals.

3.2. Fairness considerations

In this study, we adopt two complementary fairness approaches: input fairness and outcome fairness (Gutjahr, 2023). In both cases, we compare socioeconomically vulnerable and non-vulnerable individuals within the same age group. Thus, our analyses are conducted without age adjustment. Studies comparing fairness across different age groups, however, may employ age-adjusted methods or alternative indicators (e.g., years of life lost) to better capture differences in life expectancy. For outcome fairness, we use mortality rates as the primary health outcome (Goldstein and Lee, 2020), as death represents the most severe consequence of the pandemic and can be reduced through vaccination (Norheim and Asada, 2009). For input fairness, vaccines are treated as the key resource for controlling the pandemic (Hou et al., 2021). Inequality is assessed by the proportion of the population without access to vaccines, maintaining conceptual alignment with the outcome measure and capturing disparities in the distribution of this essential public health resource.

For both fairness indicators, we quantify inequality using the Gini coefficient. This widely recognized measure, although primarily defined to assess inequalities (Gini, 1914), has also been applied to health disparities (Leclerc et al., 1990; Berndt et al., 2003; McGregor et al., 2019). The Gini coefficient has several advantages, including a bounded scale (0–1), interpretability, and comparability across populations (Coulter, 2019). By applying it to mortality rates and the percentage of the population without access to vaccines, we can assess how health outcomes and vaccines are distributed across socioeconomic groups. Alternative indices, such as the Atkinson and Theil measures, are also considered. However, given our model with two vulnerability groups within each age cohort and our focus on proportional improvements rather than detailed distributional analysis, the Gini coefficient is simpler, more interpretable, and sufficient.[1]

The fairness indicator (FI) for each group is formulated as $FI = (1-G)\times 100$, so the lower Gini coefficient (G) results in higher fairness. Eq. (4) provides the formulation for the FI, where f_i (or v_i) denotes the fatality rate (or the unvaccinated percentage of the population) of the ith socioeconomic group, and N is the number of levels of socioeconomic vulnerability (in our model, $N = 2$). The socioeconomic groups are placed in ascending order of fatality rates (or unvaccinated percentages).

$$FI = (1-G)\times 100 = \left(1-\frac{\sum_{i=1}^{N}(2i-N-1)x_i}{N\sum_{i=1}^{N}x_i}\right)\times 100, \quad x_i = \begin{cases} f_i & \text{for Outcome Fairness} \\ v_i & \text{for Input Fairness} \end{cases} \tag{4}$$

4. Parameter estimation and model validation

Validation begins by checking whether the simulation accurately represents the conceptual model and complies with the model's objectives. The goal is to eliminate inconsistencies between the model and the dynamic hypothesis by examining equations and functions (Barlas, 1996). Structural validity is ensured by verifying the operational

[1] While absolute values differed slightly for the Atkinson and Theil indices, the overall trends remained consistent, confirming that the simpler Gini coefficient is adequate for our two-group analysis.

Table 2
Model parameters.

Parameter	Value	Source[a]
age multiplier Ci[Age]	[0.8, 0.9, 1]	Gimma et al. (2022)
elderly multiplier IFR[Variant]	[55, 100, 200]	CDC (2023), Sorensen et al. (2022)
middle-age multiplier IFR[Variant]	[12, 15, 25]	CDC (2023), Sorensen et al. (2022)
immunity duration post-infection	210	Hall et al. (2021)
immunity duration post-vaccine[Vax]	[0, 20, -]	Calibration
Ci change[Variants]	[1, 1.2, 1.5]	Calibration
IFR change[Variants]	[1, 1.5, 1.85]	Calibration
incubation times for variants[Variants]	[5, 3, 4]	Ahmad et al. (2022)
infectious period	10	NHS England (2023)
infectious period post-vaccine	5	Garcia-Knight et al. (2022)
reference Ci	0.48	Calibration
reference IFR	0.004	Calibration
perception decrease time	80	Calibration
perception increase time	21	Calibration
initial responsiveness[Age]	[0.0055, 0.025, 0.016]	Calibration
Alpha variant start day	230	UKHSA (2021)
Delta variant start day	410	UKHSA (2021)
variant replacement time	100	UKHSA (2021)
pandemic start day	0	Lillie et al. (2020)
vaccine start day	314	DHSC (2021)
second dose delay	56	NHS England (2021)
vaccine impact on Alpha Ci[Vax]	[1, 0.38, 0.12]	PHE (2021a)
vaccine impact on Delta Ci[Vax]	[1, 0.4, 0.15]	PHE (2021b)
vaccine impact on Alpha IFR[Vax]	[1, 0.6, 0.2]	PHE (2021a)
vaccine impact on Delta IFR[Vax]	[1, 0.65, 0.35]	PHE (2021b)
vaccine impact on infectivity	0.55	Harris et al. (2021)
vulnerability multiplier IFR[SE]	[1.45, 1]	OHID (2025b)
vulnerability multiplier Ci[SE]	[1.5, 1]	Beale et al. (2022)
vulnerability multiplier hesitancy[SE]	[2.1,1]	ONS (2023b)
vaccine hesitancy [Age]	[0.009, 0.024, 0.06]	ONS (2021b)
pandemic learning sensitivity	−0.8	Calibration
minimum fatality multiplier	0.3	Calibration
cumulative cases for pandemic learning	0.015	Calibration
pandemic fatigue sensitivity[Age]	[0.1, 0.7, 1.2]	Calibration
quarantine multiplier[Lockdown]	[0.8, 0.55,0.7]	Calibration
quarantine start time [Lockdown]	[55, 230, 342]	Gimma et al. (2022)
quarantine end time [Lockdown]	[126, 308, 403]	Gimma et al. (2022)

[a] CDC: Centers for Disease Control and Prevention, NHS: National Health Service, UKHSA: UK Health Security Agency, DHSC: Department of Health and Social Care, PHE: Public Health England, OHID: Office for Health Improvement and Disparities, ONS: Office of National Statistics.

consistency of the mathematical equations and the unit consistency of all variables. Model parameters have real-world equivalents, and assumptions or simplifications are stated.

Several model parameters are derived from a comprehensive review of the literature. Table 2 lists their numerical values and corresponding sources. Others are calibrated using data from the first 600 days of the COVID-19 pandemic in England. Four main datasets inform the calibration: (i) daily infections by age (UKHSA, 2025), (ii) daily deaths by age (UKHSA, 2025), (iii) weekly deaths by socioeconomic vulnerability (OHID, 2025a), and (iv) cumulative first- and second-dose vaccination rates by socioeconomic vulnerability (NHS England, 2025).

In Table 2, Age denotes defined age groups (Elderly, Middle-aged, and Young), Vax indicates vaccination status (NoV, V1, and V2), $Variants$ index refers to COVID-19 variants (Original, Alpha, and Delta), SE represents defined levels of socioeconomic vulnerability (Vulnerable and Non-vulnerable), and $Lockdown$ denotes the three national lockdown periods. Age-related variations in Ci and IFR are incorporated into the model using multipliers. IFR values for middle-aged and elderly groups are calibrated relative to the young non-vulnerable reference, accounting for increasing comorbidity risk (Kuan et al., 2023) and variant type.

Immunity after infection lasts about 6–8 months (210 days on average) (Hall et al., 2021). For single-dose vaccination (V1), immunity is assumed to last 20 days to allow for the simulation of second-dose uptake. The second dose is assumed to provide sustained protection throughout the simulation as the earliest immunity loss, based on a six-month immunity (Doria-Rose et al., 2021), occurs close to the end of the simulation horizon at t = 550.

Both Ci and IFR increase from the Original to Alpha variant (Volz et al., 2021) and from Alpha to Delta (Lin et al., 2021). Variants also differ in incubation periods (Grant et al., 2022). As guidelines recommend a 10-day quarantine (NHS England, 2023), we assume an infectious period of 10 days. Vaccination reduces the probability of spreading the infectious virus after 5 days from symptom onset (Garcia-Knight et al., 2022; Lunt et al., 2024). There are increases in Ci for vulnerable groups, according to Beale et al. (2022). Also, vulnerable groups exhibit higher comorbidity prevalence (Knies and Kumari, 2022). A vulnerability multiplier for IFR is calculated from long-term excess mortality data in England (OHID, 2025b).

We allow for an asymmetric adjustment time for perceived risk for different age groups, similar to Lim et al. (2023). Pandemic fatigue typically emerges around six months into the pandemic (Maddock, 2020). Differences in adherence to COVID-19 requirements among IMD groups in England are not significant (ONS, 2021a), so we assume the same risk perception for different levels of socioeconomic vulnerability.

Vaccine hesitancy varies according to age and socioeconomic vulnerability. People in deprived areas are less willing to be vaccinated (Bucyibaruta et al., 2022), whereas older populations generally show more positive attitudes than younger groups (ONS, 2021c). In our model, hesitancy is assumed to be fixed across subgroups, as ONS Coronavirus and vaccine hesitancy reports (13 January–18 July 2021) (ONS, 2021b) show no clear trend among middle-aged and elderly populations. Although a modest decline is observed in younger groups, it does not affect our analysis, which focuses on the first year of the rollout. Potential increases in hesitancy after September 2021 (e.g., during the Omicron period) fall outside the scope of our simulation horizon. The impact of vaccines on Ci and IFR is informed by COVID-19 surveillance

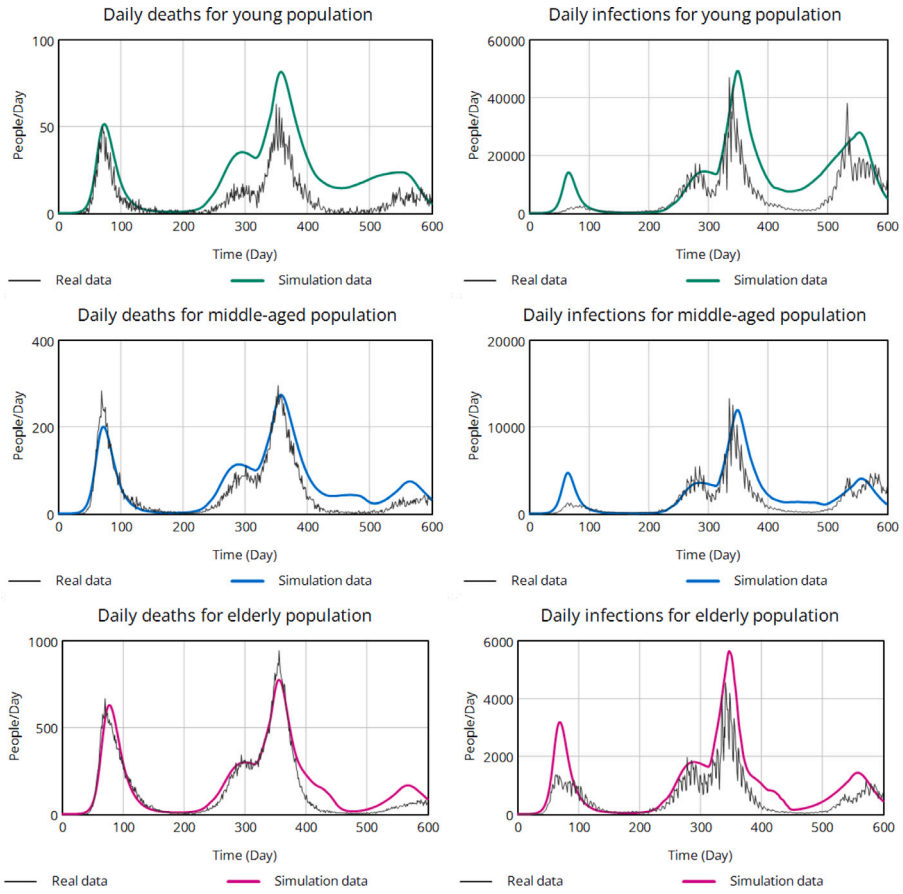

Fig. 2. Behavior validity of the model (based on data from UKHSA, 2025).

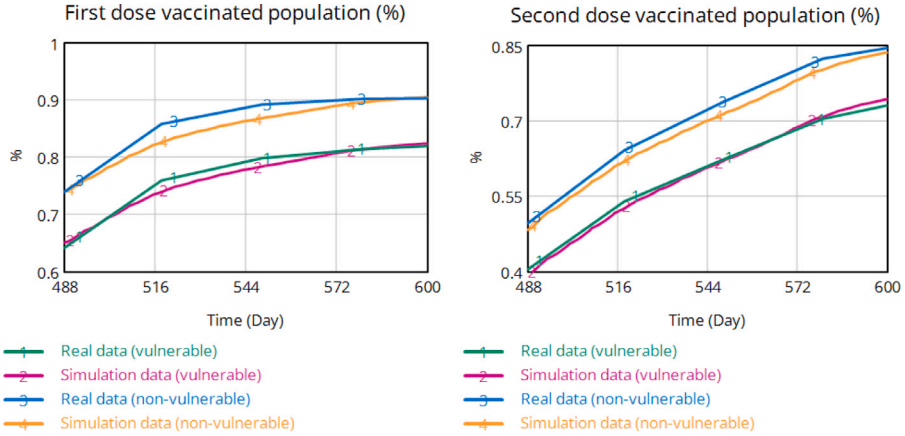

Fig. 3. Behavior validity of the model (based on data from NHS England, 2025).

reports published by Public Health England (PHE, 2021a,b). These reports provide vaccine effectiveness values for both Alpha and Delta variants as well as for the first and second doses. In our model, these values were incorporated as multipliers by calculating (1 - vaccine effectiveness). We account for the delay between doses as indicated by clinical guidelines (NHS England, 2021). The effect of vaccination on reducing infectivity uses the estimate from Harris et al. (2021).

The initial numbers of the Susceptible populations for different age and socioeconomically vulnerable groups are computed using age-stratified IMD datasets (MHCLG, 2019a). The initial values for all vaccine-related stocks are set to zero. Fig. 2 shows the model's behavior alongside the observed reference data for infections and deaths.

Vaccination coverages for the first and second doses were obtained from monthly NHS England reports (NHS England, 2025). Four reports

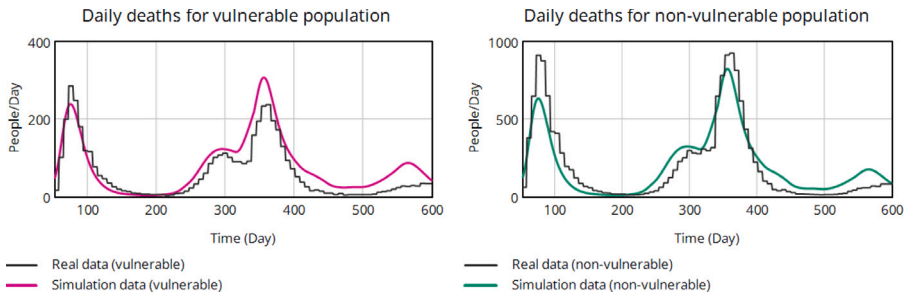

Fig. 4. Behavior validity of the model (based on data from OHID, 2025a).

corresponding to our simulation time horizon, published on 31 May 2021 (t = 488), 30 June 2021 (t = 518), 31 July 2021 (t = 549), and 30 September 2021 (t = 610), were used. Fig. 3 compares the reported data with the model outputs.

The weekly excess mortality data in England by deprivation quintile (OHID, 2025a) are converted into daily values. Fig. 4 shows deaths in vulnerable and non-vulnerable groups. To compare deaths among unvaccinated and ever-vaccinated (at least one-dose recipients) individuals in the simulation and real life, we used deaths involving COVID-19 by vaccination status in England (ONS, 2021d). Between 2 January and 2 July 2021, the proportion of COVID-19 deaths in unvaccinated individuals was 76%, while our model estimates 74.1%.

Overall, the model effectively captures the main patterns, magnitudes, and sequencing of pandemic waves in England across different age groups. Minor timing differences arise from both data limitations (e.g., under-reporting, changes in testing policy, and reporting delays) and necessary model simplifications to reduce complexity (e.g., excluding hospitalization and quarantine). Consistent with the aims of SD modeling (Randers, 1997), the focus of calibration was on reproducing the system's overall behavior and dynamics rather than matching exact peak dates, providing sufficient validity for the policy experiments.

5. Results and discussion

We first analyze the impact of implementing threshold policies with varying values for the England case study. Then, we explore two distinct what-if scenarios: one examining changes in demographic structure and the other investigating variations in socioeconomic vulnerability.

Evaluation of threshold policy

We employed different threshold values to assess how prioritizing socioeconomically vulnerable groups within different age cohorts influences the fairness and effectiveness of vaccine allocation strategies, as discussed in the Vaccination Modeling section. We use the number of deaths after the start of vaccination and the input and outcome fairness indicators as our main performance measures. The goal is to reduce the number of preventable deaths while enhancing vaccine distribution fairness based on socioeconomic vulnerability.

In the base run, with a threshold value of zero, vaccine allocation is based solely on age prioritization, without considering socioeconomic differences. This approach reflects the actual vaccination policy used in most countries, including the UK. Alternatively, by implementing a threshold policy, vaccines are initially allocated to vulnerable individuals within each age group. Once the percentage of vaccinated individuals in the vulnerable group meets the defined threshold, the remaining population within the same age group begins receiving vaccinations.

Fig. 5 illustrates the changes in the fairness indicators and the number of deaths following vaccination with varying threshold values. Scenarios are evaluated with increments of 10%, whereas the maximum threshold value is set to 70% to account for the rates of vaccine hesitancy between sociodemographic groups. If we only compare the base runs in different age groups, the elderly population shows a higher number of deaths, which is mainly due to their significantly higher IFR, despite having fewer infectious contacts (Ci). The middle-aged population exhibits the lowest values for both outcome and input fairness indicators in the base run. This group lies between the young and elderly populations in terms of IFR and Ci and shows the greatest disparity between vulnerable and non-vulnerable individuals in both deaths and vaccine access compared to other age groups.

As the threshold values increase, outcome fairness indicators improve consistently across all age groups, while the number of deaths decreases. This leads to vaccination policies that are more effective and fairer in outcomes, visible in more evenly distributed mortality rates across vulnerable groups and a more even vaccine allocation between vulnerable and non-vulnerable groups. Although the figure does not explicitly depict deaths by vulnerability status, the underlying mechanism can be explained by higher Ci values among socioeconomically vulnerable individuals, which increase their exposure to infection and consequently their risk of death. By prioritizing vaccination for these groups, we not only protect individuals but also indirectly reduce overall virus transmission within the community. On the other hand, input fairness indicators generally increase with higher thresholds across all age groups. However, at threshold 0.7, a decline is observed for the young population, although values remain above the base run. At this threshold, vaccines are allocated disproportionately to the vulnerable individuals, resulting in their vaccination rate exceeding that of the non-vulnerable individuals. While the overall impact remains mortality-reducing, this distribution results in a decline in input fairness.

Similar to the base run, for all threshold values, vulnerable populations become eligible for the first dose at t = 314 (the start of the vaccination), while there is a waiting period before administering the second dose. However, the threshold application delays the vaccination for non-vulnerable groups. Fig. 6 illustrates an example of the delay in starting the vaccination of the non-vulnerable young population and the resulting change in the daily deaths as the threshold rises from 0 (base run) to 0.7. Applying a threshold value of 0.7 significantly reduces the death peaks for the vulnerable population compared to the base run. Although a slight increase in daily deaths is observed for the non-vulnerable group (at the first peak), overall mortality decreases, and socioeconomic-based fairness indicators improve. Table 3 presents the reduction in deaths and the improvement in fairness when applying a threshold of 0.7, compared to the base run. It clearly illustrates that a fairer distribution of vaccines—through the prioritization of vulnerable individuals across all age groups—reduces fatalities.

Applying a threshold-based vaccination strategy to prioritize socioeconomically vulnerable individuals can simultaneously improve both fairness and effectiveness. The highest threshold value in our model (0.7) produces the greatest levels of outcome fairness, input fairness, and effectiveness across all age groups, except the young population, for which the thresholds yielding the best outcomes for different fairness indicators vary slightly. Although input fairness is not at its highest value for this group at the threshold of 0.7, it still

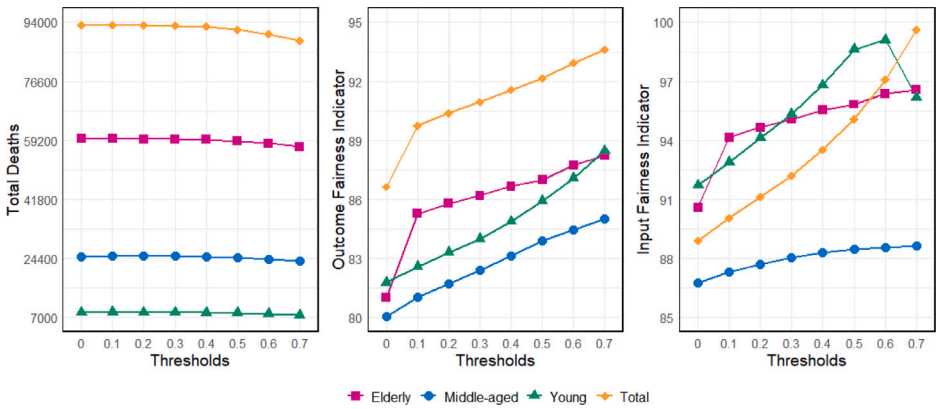

Fig. 5. Fairness indicators and total deaths by different thresholds.

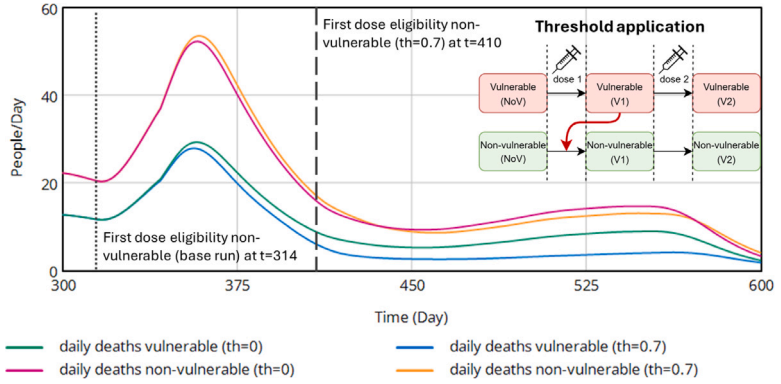

Fig. 6. Daily deaths and eligibility for the non-vulnerable young population.

Table 3
Comparison of threshold = 0.7 policy and base scenario across age groups.

Age group	Change in deaths	% Change in deaths	% Change in outcome fairness	% Change in input fairness
Old	−2515	−4.2%	8.9%	6.6%
Middle-aged	−1303	−5.2%	6.2%	2.2%
Young	−815	−9.7%	8.2%	4.9%
Total	−4634	−5.0%	8.1%	12.1%

remains substantially above the base run. Simultaneously, deaths are reduced by 9.7%. Carefully selecting reasonable thresholds, tailored to the specific sociodemographic structure, is thus critical when designing such policies. Alternative groupings of IMD quintiles to define the vulnerable group (e.g., combining the first two quintiles) could change the magnitude of observed effects. However, the main findings, including the disproportionate impact on the vulnerable group and the benefits of threshold-based prioritization, remain robust. This study does not aim to find the optimal threshold, but to show how such approaches can improve fairness and reduce mortality in future pandemics. Our findings extend the findings of Islam et al. (2021) and Chen et al. (2022), who found a prioritization strategy has a positive effect on fairness distribution, by considering the value of thresholds and the effect on a variety of fairness indicators.

It is noteworthy to mention that some studies highlight trade-offs that are less prominent in our findings. Stafford et al. (2023) identified a notable trade-off between equity and reducing disease burden under limited vaccine supply, although they found that this trade-off diminished as vaccine availability increased. Vahdani et al. (2023) also noted that while fair vaccine distribution improves social satisfaction, it may not effectively control pandemics. Unlike these studies, our analysis shows that fairness improvements can still be achieved even with constrained vaccine supplies at the early stages of a vaccination campaign, underscoring the potential of socioeconomic vulnerability-based strategies to improve fairness and effectiveness.

Effect of different demographics

We adjust the age demographics while keeping the total population and the daily vaccinated population percentage constant, and evaluate its potential effects on England. We select three representative demographic scenarios: one based on Japan, which has the oldest population, one based on Niger, which has the youngest, and one based on the world average. Daily vaccine allocations across age groups are then adjusted according to these revised age distributions. Table 4 depicts the age demographic differences for the selected scenarios, and the distribution of deaths across age groups in the absence of vulnerability-based prioritization (i.e., threshold = 0).

Fig. 7 illustrates the impact of threshold policies on demographic scenarios (i.e., demographic characteristics similar to the World Average, to Japan, and to Niger). When comparing these scenarios for the base run, total deaths are highest in the World average scenario, followed by England, Japan, and Niger. The demographic structure of the World average has substantial proportions of both young and elderly individuals. The young facilitate the spread of the disease, while the elderly contribute to higher mortality. The Japan scenario,

Table 4
Population and death distribution across different demographics for threshold = 0.

Demographic	Population			Deaths		
scenarios	Old	Middle-aged	Young	Old	Middle-aged	Young
Japan	19%	31%	50%	75%	20%	5%
England	11%	29%	60%	64%	27%	9%
World average	6%	23%	71%	54%	31%	15%
Niger	2%	13%	85%	28%	36%	36%

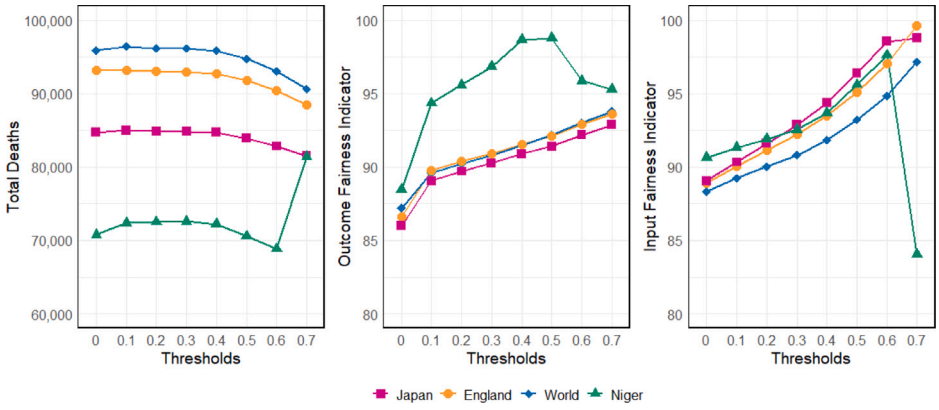

Fig. 7. Fairness indicators and total deaths by different demographic scenarios.

despite having the oldest population, experiences limited transmission due to its low proportion of young people, further reducing mortality. Predominantly young population in the Niger scenarios accelerates disease spread; however, the low IFR maintains total deaths at the lowest level. These results highlight the complex dynamics between demographic groups in disease transmission: younger populations may drive the spread, but older individuals suffer the most severe outcomes. Outcome fairness varies with age demographics for the base run, with older populations exhibiting lower fairness (greater inequality) as they are disproportionately affected by higher mortality rates. Input fairness, however, is lowest in the World average scenario, as higher deaths reduce the proportion of vulnerable individuals demanding vaccination, thereby lowering coverage in this group. In contrast, younger populations, such as Niger, include a larger total number of vulnerable individuals (14% for the elderly, 16% for the middle-aged, 21% for the young), which increases their relative vaccine demand. As these individuals are vaccinated, coverage disparities between vulnerable and non-vulnerable groups decrease, resulting in higher input fairness.

In Japan, England, and the World average scenarios, outcome and input fairness indicators improve consistently with higher thresholds. However, their impact on total mortality becomes noticeable beyond the threshold of 0.4. The Niger scenario, however, shows a distinct pattern due to its predominantly young population, which drives higher and earlier infection peaks while keeping the mortality rate low. When vaccination begins (t = 314), many individuals are already naturally immune as a result of these infection peaks. This reduces effective vaccine demand and results in vaccine wastage, because in the model, only susceptible individuals generate demand (see supplementary material). Despite the vaccine wastage, mortality reduction becomes apparent around thresholds 0.5–0.6. Outcome fairness increases up to the threshold of 0.5 as vaccination help balance mortality among vulnerable groups. However, beyond this point, mortality begins to shift toward non-vulnerable individuals. Achieving 70% coverage in the vulnerable population (threshold of 0.7) substantially delays vaccination among non-vulnerable individuals, reducing input fairness and increasing mortality.

Table 5 presents the changes in total deaths and fairness across demographic scenarios for threshold = 0.7, compared to the base run. All scenarios are calibrated to England's parameters; thus, results should be interpreted as counterfactual simulations illustrating how demographic structure alone can alter epidemic dynamics and fairness. The effectiveness of a threshold policy depends on the availability of vaccine-eligible individuals. In young populations with high natural immunity at the time of vaccine rollout, high thresholds may be less effective, while in populations with balanced age distributions, effects are observed more rapidly. Age structure and the susceptible population are therefore critical in determining threshold impact.

Effect of different levels of socioeconomic vulnerability

Similar to the age demographics analysis, we examine the impact of varying socioeconomic vulnerability ratios. While keeping the total population, daily age-specific vaccination capacities, and age group distributions unchanged, we adjust the proportion of socioeconomically vulnerable populations with increments of ±20% and ±50% within each age group. According to Table 6, which summarizes the simulation results for base runs, as the proportion of the vulnerable population grows, their share of total deaths also increases. For example, when the proportion of vulnerable individuals rises by 50% above the base run, they make up 28% of the total population but account for 40% of all deaths. This illustrates the pandemic's disproportionate impact on vulnerable groups and emphasizes the need for targeted interventions.

The simulated impact of different threshold policies on the number of deaths and the fairness indicators for different proportions of vulnerable populations is given in Fig. 8. As shown in this figure, the higher proportion of vulnerable individuals leads to higher deaths, which is not surprising as socioeconomically disadvantaged groups face higher exposure and infection fatality risks. As the proportion of vulnerable individuals increases, deaths are no longer confined to a small minority but extend across a broader segment of the population. This slightly increases outcome fairness. At the same time, infections and deaths rise within the vulnerable group, while some individuals become naturally immune or die before vaccination, reducing the effectiveness and equity of vaccine allocation. Consequently, input fairness slightly declines with higher vulnerability ratios.

The threshold policy consistently increases both outcome and input fairness by prioritizing high-risk (vulnerable) individuals, reducing mortality inequality, and improving vaccine allocation. It also lowers total deaths, with the effect becoming sharper as the vulnerable population increases. However, when the vulnerable population is very

Table 5
Comparison of threshold = 0.7 policy and base scenario across different demographics.

Demographic scenarios	Change in deaths	% Change in deaths	% Change in outcome fairness	% Change in input fairness
Japan	−3213	−3.8%	8.0%	10.9%
England	−4634	−5.0%	8.1%	12.1%
World average	−5305	−5.5%	7.6%	10.0%
Niger	10,612	15.0%	7.7%	−7.3%

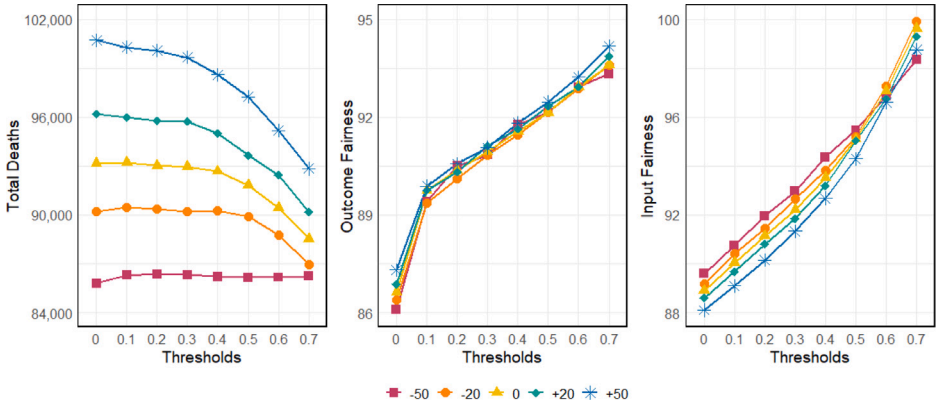

Fig. 8. Fairness indicators and total deaths by different vulnerability ratios.

Table 6
Population and death distribution across different vulnerability ratios for threshold = 0.

Change in vulnerability ratio	Population		Deaths	
	Vulnerable	Nonvulnerable	Vulnerable	Nonvulnerable
−50%	9%	91%	16%	84%
−20%	15%	85%	24%	76%
0	19%	81%	29%	71%
+20%	23%	77%	33%	67%
+50%	28%	72%	40%	60%

small (−50% scenario), the impact on total deaths is limited or slightly reversed, as vaccination of non-vulnerable individuals is delayed while transmission continues. Across scenarios, the best-outcome threshold is generally 0.7; in the case of a 50% reduced vulnerable population, fairness still improves, whereas total deaths show minimal change or a slight increase due to the small size of the vulnerable group.

Table 7 presents the reduction in deaths and improvement in fairness indicators when applying a threshold of 0.7, compared to the base scenario. The most significant number of lives saved occurs in the scenario in which the population has 50% more vulnerable individuals, resulting in a reduction of 7873 deaths. Meanwhile, the improvement in the outcome fairness indicator shows a similar pattern of around 8% between scenarios. In larger vulnerable populations, the threshold policies effectively save more lives, while the improvement in fairness is limited. Input Fairness initially rises by about 3% when moving from the −50% to the −20% vulnerable scenario and then stabilizes around 12% for higher vulnerable population levels.

6. Conclusion

This research evaluates vaccine prioritization policies that not only enhance fairness and equity but also reduce COVID-19 mortality. To achieve this, we examined the impact of incorporating socioeconomic vulnerability factors into age-based vaccine prioritization—an approach widely adopted by many countries during the pandemic. Existing vaccination frameworks primarily emphasize health-related criteria, such as age and co-morbidities, often overlooking broader social determinants of health. We argued that this conventional approach is insufficient, as it considers only age and medical vulnerability when allocating limited vaccine resources. Evidence indicates that socioeconomic factors play a significant role in vulnerability to the pandemic and should therefore be integrated into prioritization strategies. In our model, socioeconomic vulnerability groups derived from the IMD, which includes indicators such as income, employment, health, education, housing, crime, and environmental conditions, serve as a proxy for social determinants of health. Relevant parameters for each group are calibrated to real-world data, enabling the model to capture the disparities between vulnerable and non-vulnerable populations.

Our results suggest that threshold-based prioritization offers governments a more effective and fair approach to vaccine allocation. The conventional strategy of vaccinating individuals within a priority group before extending vaccines to the next group may unintentionally delay protection for large segments of the population, leading to higher mortality. By contrast, starting vaccination of non-vulnerable individuals once a certain proportion of the vulnerable population is covered can reduce total deaths, while also improving outcome and input fairness. This has several implications for real-world policy, as outlined below.

Flexibility under resource constraints: Vaccine supply during pandemics is often limited and uncertain. Threshold-based strategies allow governments to avoid bottlenecks caused by vaccine hesitancy or logistical challenges in reaching the most vulnerable. Once the threshold is met, resources can be reallocated to accelerate a broader roll-out without compromising the protection of high-risk groups.

Adaptability to diverse demographic contexts: Sensitivity analyses indicate that the benefits of threshold-based prioritization are robust for populations with balanced age distributions or varying proportions of vulnerable individuals. However, in predominantly young populations, such as Niger, lower thresholds may also be important. Both age structure and vaccine eligibility should be carefully considered when evaluating the effectiveness of this approach, highlighting its context-specific applicability across countries with diverse demographic and healthcare settings.

Balancing fairness and effectiveness: Incorporating fairness metrics such as the Gini index provides policymakers with a quantitative way to evaluate trade-offs between minimizing deaths and ensuring both input and outcome fairness. This dual focus can enhance transparency

Table 7
Comparison of threshold = 0.7 policy and base scenario across vulnerability ratios.

Vulnerability ratio	Change in deaths	% Change in deaths	% Change in outcome fairness	% Change in input fairness
−50%	444	0.5%	8.4%	9.8%
−20%	−3280	−3.6%	8.3%	12.0%
0	−4634	−5.0%	8.1%	12.1%
+20%	−5997	−6.2%	8.1%	12.1%
+50%	−7873	−7.8%	7.9%	12.1%

and public trust, which are essential for compliance with vaccination campaigns.

Operational guidance for governments: Beyond general prioritization principles, our model can serve as a decision-support tool. Governments can calibrate the threshold value to their local circumstances—taking into account vaccine supply, distribution capacity, demographic structure, timing of the vaccination, and social acceptability—thereby tailoring strategies to their specific context while still benefiting from the general principle we identify. As stated by Mamelund and Dimka (2021b), pandemics like COVID-19 or Spanish Flu disproportionately affect different socioeconomic groups. Since the IMD is an area-based indicator derived from Lower Layer Super Output Area (LSOA) data (MHCLG, 2019b,c) and can be aggregated where needed, socioeconomic vulnerability can be incorporated into prioritization frameworks alongside medical risk without identifying or stigmatizing individuals.

Using an SD model based on the SEIR epidemiological framework, we first calibrated the model with data from England to align simulation outputs with historical trends. England was chosen due to data availability and the significant disparity in health access between wealthier and poorer populations. We then proposed an age-based vaccine allocation approach that prioritizes socioeconomically vulnerable individuals within each age group. A threshold-based system, defined by the proportion of vaccinated individuals within the vulnerable subgroup, triggers vaccine administration for the rest of the age group. Various thresholds were evaluated to assess fairness and mortality reduction, and the model was further tested by adjusting age demographics and vulnerability levels to validate results across different contexts. The main outcomes of our study are as follows:

(i) Higher thresholds enable a better balance between fairness and mortality reduction across all age groups in England. Among our simulations, a threshold value of 0.7 consistently provided the best results. Higher thresholds were not tested due to concerns about vaccine hesitancy within the population.

(ii) Populations with a relatively large share of elderly people experienced greater health inequalities, however, not necessarily higher total mortality. Of course, the total mortality is affected directly by the proportion of elderly individuals (higher IFR) but also indirectly by the younger population (higher Ci), resulting in a dynamic interplay. This underscores the influence of age structure on both pandemic severity and fairness outcomes.

(iii) The effectiveness of a threshold-based policy depends on the availability of vaccine-eligible individuals. In predominantly young populations with high levels of natural immunity at the time of vaccine rollout, higher thresholds may be less effective, whereas in populations with more balanced age distributions, threshold effects are observed more rapidly.

(iv) Larger socioeconomically vulnerable populations led to higher total deaths but also a higher outcome fairness indicator in the base run (no prioritization). This seemingly counterintuitive result is attributed to the increased visibility and access to vaccinations for vulnerable groups when they constitute a larger proportion of the population. However, infections and deaths also rise within the vulnerable group, and some individuals acquire natural immunity or die before vaccination, which reduces the equity of vaccine allocation. However, implementing threshold policies consistently improved fairness across all vulnerability ratios.

This study offers valuable insights for policymakers, highlighting the complex interaction between age, socioeconomic vulnerability, and vaccination strategies in shaping pandemic outcomes. Prioritizing socioeconomically vulnerable groups not only benefits these individuals directly but also indirectly reduces overall disease transmission, ultimately lowering total deaths. The findings challenge the assumption that equity and efficiency in vaccine distribution are conflicting goals; by incorporating socioeconomic factors into prioritization strategies, the study demonstrates how a fairer vaccine allocation can simultaneously improve equity and decrease overall mortality. Nonetheless, the best-outcome threshold policies and their effects on fairness and mortality underscore the need for tailored vaccination strategies that take into account the unique characteristics of each population.

One limitation of this study is the exclusion of testing and hospitalization. Although incorporating these dynamic elements may improve the accuracy of the results, this also significantly increases model complexity. We also assume that vaccine demand is driven solely by susceptible individuals. In reality, some infected or recovered people also receive vaccines, either unintentionally due to undetected cases or intentionally after a waiting period determined by health authorities. Any leftover vaccine doses from the previous day (if any) are not carried over in our model. We evaluate only socioeconomic vulnerability-based fairness rather than between age groups. Comparisons of mortality outcomes rely on absolute differences within each age group. To maintain conceptual clarity, analytical feasibility, and ease of practical implementation, we included three age groups, each with only two socioeconomic vulnerability categories.

Future research could incorporate hospitalization into the model to extend the fairness analysis to severe illness outcomes and to evaluate healthcare system resilience. Studies could also refine assumptions about vaccine allocation, considering strategies for reallocating unused vaccines. Prioritization strategies could also be expanded by introducing allocation thresholds between age groups, enabling the inclusion of an age-based fairness indicator alongside socioeconomic vulnerability. Alternative outcome metrics such as Disability-Adjusted Life Years (DALYs) or Quality-Adjusted Life Years (QALYs) could offer a more comprehensive assessment of mortality impacts and fairness. Finally, future work could investigate how it may be feasible to subdivide age and socioeconomic categories into finer gradients and extend the analysis to other regions by recalibrating the model with local epidemiological and demographic data.

CRediT authorship contribution statement

Nezihe Nazli Gul: Writing – original draft, Visualization, Validation, Software, Methodology, Formal analysis, Data curation, Conceptualization. **Saeed Taheri:** Writing – review & editing, Validation, Software, Methodology, Formal analysis, Conceptualization. **Sander de Leeuw:** Writing – review & editing, Supervision, Funding acquisition, Conceptualization. **Ramez Kian:** Writing – review & editing, Formal analysis, Conceptualization.

Ethics approval

This study used only publicly available, anonymized data and did not involve human participants or animals directly. Therefore, ethics approval was not required

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.socscimed.2025.118918.

Data availability

We use publicly available data from GOV.UK.

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