Social Science & Medicine 383 (2025) 118352

Contents lists available at ScienceDirect

Social Science & Medicine

journal homepage: www.elsevier.com/locate/socscimed

How to incorporate social vulnerability into epidemic mathematical modelling: recommendations from an international Delphi

Megan Naidoo[a,b,*], Whitney Shephard[c], Nokuthula Mtshali[d], Innocensia Kambewe[e], Bernedette Muthien[f], Nadia N. Abuelezam[g], Miguel Ponce-de-Leon[h], Daniel A.M. Villela[i], Romulo Paes-Sousa[i], Wirichada Pan-ngum[j], David Dowdy[k], Stephen S. Morse[l], Daiana Pena[b], Lorena G. Barberia[m], Rein M.G.J. Houben[n], Pedro Arcos González[o], Jamela E. Robertson[p], Rachid Muleia[q], Olanrewaju Lawal[r], Davide Rasella[b]

[a] Facultat de Medicina i Ciències de la Salut, Universitat de Barcelona (UB), Barcelona, Spain
[b] Barcelona Institute for Global Health Campus Clínic, Hospital Clínic - Universitat de Barcelona, Barcelona, Spain
[c] Child Mind Institute, New York City, United States of America
[d] Tiko Africa, Johannesburg, South Africa
[e] University of Witwatersrand, Johannesburg, South Africa
[f] University of the Free State, Bloemfontein, South Africa
[g] Michigan State University College of Human Medicine, Michigan, United States of America
[h] Barcelona Supercomputing Center, Barcelona, Spain
[i] Oswaldo Cruz Foundation, Rio de Janeiro, Brazil
[j] Mahidol-Oxford Tropical Medicine Research Unit (MORU), Faculty of Tropical Medicine, Mahidol University, Bangkok, Thailand
[k] Johns Hopkins Bloomberg School of Public Health, Baltimore, United States of America
[l] Department of Epidemiology, Columbia University Mailman School of Public Health, New York City, United States of America
[m] University of São Paulo, São Paulo, Brazil
[n] TB Modelling Group, TB Centre, London School of Hygiene and Tropical Medicine, London, United Kingdom
[o] Unit for Research in Emergency and Disaster, University of Oviedo, Oviedo, Spain
[p] Engender, Cape Town, South Africa
[q] Instituto Nacional de Saúde, Maputo, Mozambique
[r] University of Port Harcourt, Port Harcourt, Nigeria

A R T I C L E I N F O

Handling editor: Social Epidemiology Office

Keywords:
Social vulnerability
Mathematical modelling
Epidemics
Pandemics
Infectious diseases
Social determinants of health
Health equity

A B S T R A C T

Epidemic mathematical modelling plays a crucial role in understanding and responding to infectious disease epidemics. However, these models often neglect social vulnerability (SV): the social, economic, political, and health system inequalities that inform disease dynamics. Despite its importance in health outcomes, SV is not routinely included in epidemic modelling. Given the critical need to include SV but limited direction, this paper aimed to develop research recommendations to incorporate SV in epidemic mathematical modelling. Using the Delphi technique, 22 interdisciplinary experts from 12 countries were surveyed to reach consensus on research recommendations. Three rounds of online surveys were completed, consisting of free-text and seven-point Likert scale questions. Descriptive statistics and inductive qualitative analyses were conducted. Consensus was reached on 27 recommendations across seven themes: collaboration, design, data selection, data sources, relationship dynamics, reporting, and calibration and sensitivity. Experts also identified 92 indicators of SV with access to sanitation (n = 14, 6.1 %), access to healthcare (n = 12, 5.3 %), and household density and composition (n = 12, 5.3 %) as the most frequently cited. Given the recent focus on the social determinants of pandemic resilience, this study provides both process and technical recommendations to incorporate SV into epidemic modelling. SV's

* Corresponding author. Rosselló 171, Barcelona, 08036, Spain.
E-mail addresses: megan.naidoo@isglobal.org, mnaidona7@alumnes.ub.edu (M. Naidoo), shephard.whitney@gmail.com (W. Shephard), nokuthulapmtshali@gmail.com (N. Mtshali), innocensiackambewe@gmail.com (I. Kambewe), MuthienBL@ufs.ac.za (B. Muthien), abueleza@msu.edu (N.N. Abuelezam), miguel.ponce@bsc.es (M. Ponce-de-Leon), daniel.villela@fiocruz.br (D.A.M. Villela), romulo.paes@fiocruz.br (R. Paes-Sousa), pan@tropmedres.ac (W. Pan-ngum), ddowdy1@jhmi.edu (D. Dowdy), ssm20@columbia.edu (S.S. Morse), daianapena1927@gmail.com (D. Pena), lorenabarberia@usp.br (L.G. Barberia), Rein.Houben@lshtm.ac.uk (R.M.G.J. Houben), arcos@uniovi.es (P. Arcos González), info@engender.org.za (J.E. Robertson), rachid.muleia@ins.gov.mz (R. Muleia), olanrewaju.lawal@uniport.edu.ng (O. Lawal), davide.rasella@isglobal.org (D. Rasella).

https://doi.org/10.1016/j.socscimed.2025.118352
Received 3 February 2025; Received in revised form 23 May 2025; Accepted 30 June 2025
Available online 30 June 2025

inclusion provides a more holistic view of the real world and calls attention to communities at risk. This supports forecasting accuracy and the success of policy and programmatic interventions.

1. Introduction

1.1. The importance of epidemics and modelling

Society has never been more interconnected. With rapid intercontinental trade, transportation, and the proliferation of urban centres, infectious diseases have the potential to develop into far-reaching epidemics or pandemics (Neiderud, 2015). The global spread of COVID-19 brought this threat to life, illustrating how quickly communities around the world can suffer from an emerging infectious disease. In just two years, global life expectancy decreased by 1.6 years. The pandemic resulted in 15.9 million deaths from 2020 through 2021 – not just from the disease itself, but also from the ensuing social and economic challenges (GBD 2021 Demographics Collaborators, 2024).

It is of the utmost importance that researchers understand how infectious diseases affect diverse communities and determine which interventions can mitigate disease impact (Sierra et al., 2023). One approach is to use mathematical models. Epidemic mathematical modelling plays a crucial role in understanding and responding to infectious disease outbreaks. They aid in preparedness and response by describing the course of an outbreak and how the disease, and any interventions, may affect individuals and populations (White, 2017; Diekmann et al., 2012).

Mathematical models are simplified representations of the real world. The first disease model was developed by Daniel Bernoulli in 1760 to understand the effect of smallpox inoculation on mortality (Bernoulli, 1760). Kermack and McKendrick's 1927 SIR framework, which simulates a population transitioning between susceptible, infected, and recovered states, was a seminal step in disease modelling and forms the basis of many modern models (Kermack and McKendrick, 1927). Today, there are several types of models, including compartmental, metapopulation, network, and agent-based models (ABM). While they may vary in methodologies, overall, mathematical models allow researchers to predict, project, and/or simulate a disease outbreak in time and space (White, 2017; Diekmann et al., 2012).

Modelling has become a mainstay in epidemic preparedness and response. Therefore, it is necessary models capture the social vulnerabilities that impact disease progression and health outcomes.

1.2. What is social vulnerability?

Social vulnerability (SV) describes a community's ability to prepare for, respond to, and recover from disasters such as an epidemic (Cutter and Finch, 2008). More specifically, SV is a multidimensional concept that encompasses limited resilience during a crisis as a result of social, economic, and health system inequalities (Flanagan et al., 2011; Cutter and Finch, 2008). SV is similar to the social determinants of health (SDH) in that social conditions impact health outcomes, but it relates particularly to the needs of a crisis, such as equitable access to personal protective equipment during an epidemic.

SV highlights that epidemics are not solely a result of biology but include the social conditions that allow disease to proliferate. Importantly, SV is not reflective of an individual's failing but rather a community characteristic as a result of historical and structural injustices. While no one is entirely safe from the threat of an epidemic, socially vulnerable populations often experience disproportionate rates of disease and death due to this structural inequity (Mubangizi, 2021; Kantamneni, 2020).

There is work underway to ensure SV is central to disaster research (Li and Wang, 2022; Ran et al., 2020). The United States' (US) Centers for Disease Control and Prevention (CDC) developed a Social Vulnerability Index (SVI) to determine community resilience. Four SV categories were identified: socioeconomic status, household composition, racial and ethnic minority status, and housing type and transportation (Flanagan et al., 2011). A review revealed that health and medicine SV indices most commonly incorporated education, socioeconomic status such as income or wealth, and household composition. Other interesting categories of note included social connection and capital, social engagement, personal attitudes and expectations, and political stability (Mah et al., 2023). Specific to infectious diseases, other researchers considered vulnerable populations, SDH, culture, knowledge, attitudes, and practices (KAP), geographic location, and contact and movement behaviour as contributors to SV (Naidoo et al., 2024). However, this list is not exhaustive, and there is room to further define and measure SV (Cutter and Finch, 2008).

The aforementioned indicators (and more) affect disease dynamics and health outcomes (Dasgupta et al., 2020; World Health Organisation, 2008). Therefore, it is vital that epidemic mathematical models incorporate SV. Many models, however, do not extensively consider SV in their design, development, or interpretation (Abuelezam et al., 2023; Tizzoni et al., 2022; Williams et al., 2022; Bedson et al., 2021; Buckee et al., 2021; Galanis and Hanieh, 2021).

1.3. The challenges of incorporating social vulnerability into epidemic modelling

Incorporating SV into epidemic modelling can be challenging. Firstly, SV data is often unavailable or limited (Torres et al., 2021). This potentially restricts SV's integration into model equations and impacts model calibration and validation. Secondly, translating and parameterising social behaviour and culture is complex (Bedson et al., 2021). Thirdly, there is a scarcity of frameworks available to introduce socio-structural components (Zelner et al., 2022). Fourthly, the mechanisms between social vulnerabilities and model outcomes are not always known or clear (Tizzoni et al., 2022).

Despite the challenges, incorporating SV remains essential to accurately assess the impact and spread of diseases within different populations (Richard and Lipsitch, 2024; Galanis and Hanieh, 2021). Bringing attention to communities at risk is critical because when any community faces a disease threat, there is a risk to the whole population as infectious diseases are transmissible and relational. This is notable for acute respiratory infections, which — unlike HIV, sexually transmitted infections, and tuberculosis — were often seen as "equal opportunity infectors" until the COVID-19 pandemic (Zelner et al., 2022; Moran et al., 2020). Now, COVID-19 has been described as a "syndemic." Existing health inequalities intersect with and exacerbate epidemic outcomes, leading to "unequal exposure, unequal transmission, unequal susceptibility, and unequal treatment" (Bambra, 2022; Bambra et al., 2020).

As the use of mathematical modelling becomes commonplace in decision-making, the lack of SV in models may lead to ineffective responses and even widen health inequity gaps (Tizzoni et al., 2022). For example, during the COVID-19 pandemic, the success of stay-at-home mandates differed by income level in low- and middle-income countries (LMICs). Low-income earners were forced to go out and work and face exposure to infection or confront further deprivation (Bargain and Aminjonov, 2020). Without accounting for this social issue, the success of stay-at-home mandates would be overestimated. As an illustration, a model for Liberia accounted for SV in the population's stay-at-home compliance. With the necessary provisions (e.g. food, water, and chamber toilets), impoverished communities experienced a 26.0 % reduction in COVID-19 incidence compared to 9.9 % without the support to stay-at-home (Skrip et al., 2021).

SV's inclusion provides a more holistic view of real-world dynamics and makes forecasts more reliable, therefore better supporting policy and programmatic interventions (Bedson et al., 2021; Galanis and Hanieh, 2021).

1.4. Addressing these challenges

Calls have been made to more comprehensively consider SV-related indicators and highlight vulnerable populations when modelling outbreaks (Naidoo et al., 2024; Abuelezam et al., 2023; Williams et al., 2022; Zelner et al., 2022; Bedson et al., 2021; Galanis and Hanieh, 2021). Despite its importance, the inclusion of SV in epidemic modelling is not routine (Tizzoni et al., 2022; Bedson et al., 2021; Galanis and Hanieh, 2021), and practices vary (Naidoo et al., 2024). A scoping review outlined methodological and technical approaches to integrating SV in infectious diseases models. The review also revealed there is insufficient transparency around data sources, inconsistent reporting practices, limited partnerships with local experts, and a scarcity of studies that incorporate cultural indicators into models (Naidoo et al., 2024). While there are guidelines related to infectious disease modelling, SV is discussed as a broad concept (Ali et al., 2024). Guidelines and frameworks that specifically focus on equity in modelling are reviews or commentaries (Abuelezam et al., 2023; Tizzoni et al., 2022; Zelner et al., 2022; Williams et al., 2022; Bedson et al., 2021; Buckee et al., 2021; Funk et al., 2015) and highlight the need for standardised protocols (Ali et al., 2024; Bedson et al., 2021). Researchers need a clear and consistent starting point.

Given the critical need to include SV in epidemic modelling but limited direction, the aim of this paper is to develop research recommendations that can be used to incorporate social vulnerability in epidemic mathematical modelling.

2. Methods

In order to develop research recommendations, the Delphi method was deemed the most appropriate technique. Experts provide feedback in an iterative and structured approach to achieve consensus. The technique allows for anonymous responses to encourage diverse viewpoints and reduce groupthink, but leverages the value of group feedback (Humphrey-Murto et al., 2017; Thangaratinam and Redman, 2005; Linstone and Turoff, 1975). The Delphi method consists of six steps: (1) defining the research question, (2) conducting a literature review, (3) creating a questionnaire, (4) administering multiple rounds of anonymous questionnaires, (5) offering feedback between rounds, and (6) compiling and summarising the results. (Humphrey-Murto et al., 2017).

This study leveraged the online Delphi method, whereby participants responded to an online questionnaire using Google Forms. Participants were anonymous to one another to support honest responses. Names were solely used by the data analysis team to link responses through rounds. The first author (MN) aggregated the results and provided summarised feedback (median, minimum, maximum, standard deviation, and responses from inductive qualitative analysis). Participants had the opportunity to adjust their individual responses based on the feedback of the group. This process was repeated for three rounds, determined a priori as guided by the literature (Niederberger and Spranger, 2020; Thangaratinam and Redman, 2005).

A review of Delphis recommended 8–23 participants (Shang, 2023). This study aimed for a participant size of 20–25. Purposeful and snowball sampling were used to identify potential participants. A literature review and search of experts in SV, social and health equity, infectious diseases, and infectious disease mathematical modelling were conducted. For this study, experts were defined as having more than 10 years of relevant experience in field(s) related to SV, epidemiology, infectious diseases, modelling, outbreaks, epidemics, pandemics, health policy, social sciences, community health, healthcare, medicine, anthropology, and/or bioethics. Experts were able to identify with more than one area of expertise. Recruitment was also based on ensuring representation from both men and women and participation from LMICs.

A literature review of articles that referenced social justice and equity in modelling was consulted to develop the initial list of key recommendations (Abuelezam et al., 2023; Williams et al., 2022; Bedson et al., 2021; Buckee et al., 2021). The survey instrument was tested by 30 volunteers for ease of use and clarity. The first survey consisted of 22 recommendations grouped under seven themes: collaboration, design, data selection, data sources, relationship dynamics, reporting, and calibration and sensitivity. Each theme had an open-ended section where participants could add, amend, or remove recommendations. Participants rated each recommendation on a scale of one (not important) to seven (very important). Throughout the rounds, participants were also asked to develop a list of SV indicators, provide feedback on the best ways to include social vulnerability in epidemic modelling, and share insights as to which scenarios are most imperative for incorporating SV.

Consensus for inclusion in the final list was established when ≥70 % of participants rated a recommendation as ≥6 on a 7-point scale. Recommendations for which <50 % of participants provided a rating of ≥6 were dropped. Recommendations for which 50–69 % of participants selected a rating of ≥6 were added to the next round for review. In the first round, participants were asked to evaluate the initial list of 22 recommendations and could provide additional qualitative feedback. The second round comprised four recommendations that had not reached consensus in the first round, plus 14 new recommendations generated from open-ended comments. In the third round, three recommendations from the second round for which 50–69 % of participants provided a ≥6 rating were under review.

An inductive approach was used to analyse the qualitative feedback, where codes and themes were developed based on the data (Thomas, 2006). Four co-authors (MN, WS, NM, IK) independently conducted the qualitative analyses and harmonised the results. Feedback that related to modelling in general, and not specifically SV in epidemic mathematical modelling, was not included in the list of new recommendations.

3. Results

Twenty-two international and interdisciplinary experts were consulted with 100 % response rate. Thirteen (59.1 %) were men and 9 (40.9 %) were women (participants self-identified their gender). The majority of experts identified their country of origin as an LMIC (n = 13, 59.1 %) and had more than 20 years of experience (n = 13, 59.1 %). Most experts had more than one area of expertise (90.9 %). One in five experts listed epidemiology as one of their areas of expertise (n = 14, 19.7 %), with modelling (n = 11, 15.5 %) and infectious diseases (n = 10, 14.1 %) following in frequency. Seven experts worked in policy (9.9 %), 6 (8.5 %) in the social sciences, and 4 in community health (5.6 %) (see appendix A).

Experts identified 92 indicators (see appendix B). Access to sanitation (n = 14, 6.1 %), access to healthcare (n = 12, 5.3 %), and household density and composition (n = 12, 5.3 %) were the top indicators of SV to epidemics. Sex and gender (n = 11, 4.8 %), age (n = 10, 4.4 %), and access to clean water (n = 10, 4.4 %) followed (see Table 1). The most common indicator category was living conditions (n = 54, 23.7 %). Health (n = 46, 20.2 %), such as access to care and health status, was the second most common category. Other notable categories included technology and information (n = 7, 3.1 %), social protection (n = 6, 2.6 %), social discrimination and structural injustice (n = 5, 2.2 %), and outbreak-specific indicators (n = 4, 1.8 %), like access to personal protective equipment (see appendix B).

The final list comprised 27 research recommendations across seven themes (see Table 2).

In terms of the best methodological ways to incorporate SV into models, the following approaches were identified:

Table 1
Top 10 most frequent indicators among 92 indicators of social vulnerability to infectious disease epidemics (N = 228).

Indicator	n	%
Access to sanitation	14	6.1
Access to healthcare	12	5.3
Household density and composition	12	5.3
Sex and gender	11	4.8
Access to clean water	10	4.4
Age	10	4.4
Income-level	8	3.5
Migrant status (undocumented, refugee etc.)	8	3.5
Race and ethnicity	7	3.1
Education level	6	2.6
Poverty	6	2.6

- Stratify the aggregate-level model, although it may require many levels (42 % of comments).
- Add or adjust parameters, although it may limit flexibility (33 % of comments).
- Create models with individual agents and agent-specific features, such as agent-based or network models and microsimulations (25 % of comments).
- Add additional compartment(s) or state(s) (8 % of comments).

30.8 % of participants that responded to this question stated that SV should always be included in epidemic modelling. Experts qualitatively noted that SV was particularly important to include in the following scenarios:

- When the study question is linked to SV,
- When modelling heterogeneous populations (e.g., when modelling populations where there is a large social gap and therefore communities have differing risks, or when modelling how different groups respond to and are impacted by an epidemic),
- When modelling large-scale epidemics where there are subpopulations with different vulnerabilities,
- When modelling interventions,
- In contexts where there is resistance to participation,
- When modelling for seasonal assessments or preparedness plans (vs. in emergencies when time and resource constraints may not allow for complete integration).

4. Discussion

The COVID-19 pandemic highlighted the importance of considering social vulnerability in disaster resilience. Social vulnerabilities are therefore important to include in the tools we use for epidemic

Table 2
The final list of recommendations on how to incorporate social vulnerability into epidemic modelling.

Collaboration
Collaborate with stakeholders outside of the modelling field to provide expertise on social vulnerability.
Build collaborations early during model preparation and planning phases.
Ensure collaborations are multidisciplinary (e.g., including policy-makers, data providers, epidemiologists, economists, social scientists, anthropologists, community healthcare workers, etc.).
Ensure inclusive and diverse representation of collaborators from different demographic backgrounds (e.g., ethnicity, gender identity, historically marginalised populations, etc.).
Engage with the populations affected by the policy and programmatic implications of the model throughout the modelling process (e.g., when planning, designing the model, verifying data and results, reporting, etc.).
Lower the barriers to engagement (e.g., have meetings in common languages, offer co-authorship, etc.) to ensure participation is accessible and foster an environment of mutual respect between collaborators.
Design
Design the model guided by the social vulnerabilities that impact the research question and model's purpose.
Tailor the model's design to the context of the setting and/or population of study.
Engage with community and context-specific experts to understand how different social vulnerabilities may affect each other in the model.
Ensure social vulnerability indicators and their interactions are captured throughout the model's design.
Design the model to reflect patterns and histories of social vulnerability in the research question.
Data selection
Given the complexity of models and data availability, select and focus on the key social vulnerabilities and conditions relevant to the research question and model's purpose.
Use empirical evidence (e.g., peer-reviewed journal articles, reports, etc.) and engage with community- and context-specific experts and data collectors/providers to select the key social vulnerability indicators and/or populations for the model.
Data sources
Work with community members and/or experts to identify context-specific social vulnerability data sources.
Work with community and/or context-specific experts to contextualise and validate input empirical data.
Work with community and/or context-specific experts to inform initial conditions and input parameter values related to social vulnerability.
In the absence of context-specific social vulnerability data sources, evaluate the applicability of using non-context-specific data sources (e.g., using national estimates for a subnational community or using data from another country).
Evaluate and report the quality, biases, and uncertainties of social vulnerability data sources (both empirical data and community or expert opinion).
Relationship dynamics
Evaluate potential intersecting relationships between social vulnerability indicators (e.g., women and lack of access to care) and how they may impact the model's design and outcomes ("intersectionality").
When incorporating additional dynamics or interactions, evaluate if the data available is sufficient to support the added complexity.
Reporting
Provide social vulnerability data and sources, and report other considerations to ensure replicability and allow for external evaluation.
Report the limitations and assumptions related to social vulnerability indicators and dynamics in the model.
Contextualise findings and conclusions in the study population's historical and current social vulnerability conditions.
Report short- and long-term policy and programmatic implications related to social vulnerability.
Report findings and policy and programmatic implications back to the communities affected by the model's outcomes.
Calibration and sensitivity
If calibration is applicable, calibrate parameters related to social vulnerability.
Conduct sensitivity analyses of social vulnerability indicators to estimate their impact on model dynamics and outcomes.

preparedness and response, including mathematical models. In this study, 27 research recommendations across seven themes were developed to support SV's integration into epidemic modelling. These recommendations are considerations and need to be adapted for each model's context and purpose.

Incorporating social conditions into epidemic modelling is essential because it can improve the accuracy, precision, and validity of models, as disease dynamics are better characterised and parameterised to reflect real-world circumstances (Ali et al., 2024; Abuelezam et al., 2023; Bedson et al., 2021; Galanis and Hanieh, 2021; Funk et al., 2015). Furthermore, the integration of SV reveals the heterogeneity in disease burden and the differing impact of policy decisions, which supports equity-focused responses (Ali et al., 2024; Naidoo et al., 2024; Zelner et al., 2022). This aligns with this study's results, where participants highlighted the importance of considering SV when modelling heterogeneous populations and interventions. For example, during the COVID-19 pandemic, the US mortality rate was 259.9 among non-Hispanic White Americans, but in American Indian and Alaska Native communities, the mortality rate was nearly double at 495.0 (Sumibcay et al., 2024). Such stark differences in rates spotlight the need for tailored interventions.

Models have the potential to support customised, equity-focused responses by considering SV. For example, given concerns around mass unemployment as a result of lockdown measures, researchers simulated the effect housing evictions would have on COVID-19 transmission in the US. The model found evictions led to a significant rise in infections, especially in poorer neighbourhoods. These results suggested eviction moratoria could be an equitable control measure (Nande et al., 2021).

4.1. Indicators of SV

Deciding which indicators to consider is context- and disease-specific. However, experts have identified living conditions and health indicators as key considerations when developing an epidemic model. Specifically, access to sanitation, access to healthcare, and household density and composition were the top three indicators of SV. There are many ways to define and quantify these indicators. Researchers need to consider the data available as well as what definition is most relevant for the context. For example, access to health care may be defined as access to a general practitioner, available inpatient hospital beds, or supply of medication depending on the research question, disease and population under study, and data available. Age and sex and gender were also highlighted as top indicators. This is in line with other reviews, which noted a focus on these indicators (Ali et al., 2024; Naidoo et al., 2024). However, it is worth recognising that age and sex are routine demographic variables and, while important, do not necessarily represent a holistic view of SV. Given their impact on health outcomes, calls have been made to further consider behavioural, social, cultural, and historical structural factors (Naidoo et al., 2024; Bedson et al., 2021; Funk et al., 2015; Sierra et al., 2023). This study also noted social discrimination and structural injustice as pertinent to SV. Furthermore, learnings from the COVID-19 pandemic highlight outbreak-specific resources, such as access to personal protective equipment and health surveillance networks, as necessary in epidemic management (Bartoletti et al., 2024; Livingston et al., 2020). These indicators are important to consider when framing SV in epidemic modelling.

4.2. Research recommendations

Twenty-seven recommendations across seven themes were developed. The themes were collaboration, model design, data selection, data sources, relationship dynamics, reporting, and calibration and sensitivity. These considerations are discussed below.

4.2.1. Collaboration

There was an emphasis on working with stakeholders, including community representatives and, in the case of modelling national or international populations, country or international population experts. Building interdisciplinary teams, from anthropology and ethics to policy and statistics, ensures diverse perspectives are represented to facilitate effective and equitable translation of research to policy and practice. While studies have recommended stakeholder engagement (Staniszewska et al., 2021; Behrend et al., 2020; Laird et al., 2020; Grant et al., 2016) and there is movement towards participatory modelling, in reality there is limited collaboration with local experts and experts from the global south (Naidoo et al., 2024; Sweileh, 2022). Collaboration with the public ensures models, from their design to their input parameters, reflect the lived realities of communities (Staniszewska et al., 2021; Laird et al., 2020). It also strengthens the resulting policy recommendations by providing the context that influences interventions' success (Niu et al., 2021; Laird et al., 2020). Moreover, research is more likely to be embraced in policy and practice when done in partnership (Laird et al., 2020). However, extensive collaboration throughout the modelling process may not always be possible because of barriers to engagement (e.g., lack of trust, time, and resources, especially during an emergency) or participation given competing priorities (Laird et al., 2020). This highlights the need to develop and foster sustained partnerships, especially during early preparation phases. Furthermore, as one participant noted, "Even in emergencies, a 5-min call to a community leader or similar will make all the difference to the epidemiological response/s and community support for interventions needed."

4.2.2. Data sources

SV is multidimensional, so it may not be possible to include all aspects due to data availability and model complexity. For example, while it is important to have accurate numerical data that is ideally from the community of study, these data sources may not be available given the difficulties in collecting timely, high-quality data on SV (e.g., lack of investment in SV data collection, inaccessible privatised data, absence of data collection infrastructure, limited effort in collecting qualitative big data, difficulties in defining social and cultural indicators, lack of standardised SV indicators, etc.) (Kretzschmar et al., 2022; Torres et al., 2021; Cutter and Finch, 2008). Modellers may need to use proxy data from other settings, despite SV being highly context-specific. While practical, using proxy indicators may lead over- or under-estimating model outcomes (Wardle et al., 2023). In the short-term, tailoring the data to the setting under study can be achieved by working with experts and community members to validate the input data (Bedson et al., 2021). In the long-term, we need to advocate for context-specific data collection (Naidoo et al., 2024; Wardle et al., 2023).

Leveraging existing data from other fields, such as the social and behavioural sciences, and identifying ways to parameterise these data can also help mirror important SV dynamics. Moreover, advancing data sharing can help bridge the data gap (Bedson et al., 2021; Torres et al., 2021). There are also novel advancements being made in disease surveillance and data collection, like the use of social media for sentiment analysis (Mirugwe et al., 2024) or building mobility networks from cell phone data (Chang et al., 2021), which may provide valuable insights. However, there are still limitations to these new technologies. For example, to protect users' identity, cell phone data are not disaggregated by demographics (like gender) which can impact disease patterns, and the data excludes people without cell phones etc. (Buckee et al., 2021). We should continue to advocate for ethically sourced country- and subpopulation-specific data collection tools that are stratified by SV determinants and include social and behavioural questions, especially for under-represented communities (Richard and Lipsitch, 2024; Tizzoni et al., 2022). This would not only serve the modelling field, but would support broader efforts for equitable and tailored public health responses.

4.2.3. Data selection

Model complexity is another challenge that needs to be considered. Models often follow Occam's razor, where a simplified approach is favoured for model tractability and parsimony (Bedson et al., 2021). Many additional parameters can make model calibration challenging given the risk of overfitting (Bershteyn et al., 2022; Basu and Andrews, 2013). Furthermore, parameters estimated from poor quality data or added assumptions can introduce biases or uncertainty into the model. Modellers must be thoughtful and purposeful in selecting SV indicators, and they must be aware of the key SV factors affecting the population they are modelling. For example, they should consider overcrowding if that is a prominent issue in the area under study, or include race if they are modelling a racially diverse population. In addition to consulting community- and context-specific experts, statistical model selection methods can also aid in determining key indicators. While the list of SV indicators may need to be pared down, the selection should still be sufficient to convey the real-world SV experienced by the population.

4.2.4. Model design and relationship dynamics

A main type of model uncertainty is structural, whereby the model's design does not sufficiently capture real-world dynamics that impact policy and programmatic decision-making (Bershteyn et al., 2022; Jit and Brisson, 2011). Therefore, careful consideration of where and how SV indicator(s) act in the model is essential. SV should be regarded throughout the model's design and should not be assumed to affect only one point in the modelling process. Moreover, some SV indicators can have intersectional and compounding effects, which may need to be considered. For example, research into the 2014-15 Ebola outbreak in Liberia showed that co-occurring factors like displacement, disability, and food insecurity were prevalent in areas hit hardest by the disease (Stanturf et al., 2015). Furthermore, social vulnerabilities do not develop in isolation. They are often a reflection of historical context. Incorporating the patterns and histories of injustice in the design of a model (e.g., adding compartments or states for differing access to healthcare because of discrimination) acknowledges the lived experiences of marginalised populations and the structural mechanisms that impact epidemic progression (Abuelezam et al., 2023).

4.2.5. Reporting

Transparent and standardised reporting is a necessity that is not always addressed (Ali et al., 2024; Naidoo et al., 2024). The issue of reporting led to the creation of Epiforge, a general guideline for reporting of epidemic forecasting (Pollett et al., 2023). This study extends Epiforge's recommendations to include reporting SV data sources, limitations, assumptions, and, importantly, context. Contextualising a model's findings and conclusions allows the reader or listener to understand the relevant structural injustices that may have led to health disparities. This can help decrease stigma and bias that may arise from oversimplified results. Furthermore, being able to report findings and their implications back to the communities most affected requires research to be readable and understandable by the public. Data communication has become a critical component of research and should be developed as part of modellers' essential skills.

4.2.6. Calibration and sensitivity

Finally, calibration is important in developing model credibility, especially for forecasting. Calibration involves varying parameters to align the model's output to a set standard of observed data and trends. In this way, historical data informs model parameters (Abuelezam et al., 2023; Bershteyn et al., 2022). For example, lower reported incidence in external data compared with the model's outcomes may indirectly refer to limited access to testing, which is accounted for by adjusting the relevant model parameters. However, explicit attention should also be paid to include and calibrate SV-specific indicators, as suggested by this study's recommendations. Further, sensitivity analyses can help indicate the impact of SV on model dynamics and outcomes, and across social groups.

4.3. Technical approaches

Technical approaches were not the main focus of this study as the methods to adjust formulas and computational equations are indicator- and setting-specific and therefore challenging to provide general guidance. However, the qualitative results align with the need to tease out heterogeneities. Options include stratifying the model population(s), adding or adjusting input model parameters, and/or adding SV-specific features such as agent characteristics, compartments, or states. For example, modellers can develop a stratified model, one for males and another for females, with interaction between the sexes (de Boer and Lutscher, 2018), or decrease disease recovery rate to account for unsanitary facilities (Banerjee, 2019). This study's suggestions are in line with other studies' recommendations on how to incorporate social issues in infectious disease modelling (Naidoo et al., 2024; Abuelezam et al., 2023; Tizzoni et al., 2022; Andradóttir et al., 2014; Caro et al., 2012).

A recent review outlined the general methodological options to integrate SV in modelling with discussion around the relevant challenges. The most common indicators in the review were age, sex, and poverty. These indicators were modelled by stratifying the model and adding or adjusting parameter values. Specifically, modellers included age-based contact rates and matrices, developed age- and sex-structured models, and adjusted the contact, transmission, recovery, and mortality rates to account for the effects of poverty (Naidoo et al., 2024).

The review also highlighted several studies with novel approaches. For example, civic capital was incorporated into a COVID-19 model to demonstrate the impact culture has on disease mortality in Italy. Durante et al. developed a physical distancing index using principal component analysis. The index included blood donations, trust in others, and newspaper readership as proxies for belief in other's well-being and law-abidingness. This physical distancing index (ranging from zero to one) modified the transmission rate, with higher civic values corresponding to reduced mobility. If all provinces had high civic capital, the model simulated a 60 % reduction in excess deaths (Durante et al., 2021).

Another example noted in the review was a theoretical compartmental model and ABM to qualitatively illustrate fear as an adaptive behaviour in response to disease prevalence. Susceptible individuals could be "infected" with fear through contact with sick and/or scared individuals. The SIR model leveraged additional compartments and a fear-specific transmission rate to represent infection with and recovery from fear, the pathogen, or both. Fleeing behaviour was modelled with an ABM. Through a probabilistic function and two-dimensional lattice, fearful agents were coded to either flee to other patches, remove themselves from circulation through self-isolation, or do neither. With the introduction of flight, the simulated epidemic dramatically increased and spread (Epstein et al., 2008).

Finally, in calculating the force of infection, contact matrices typically focus on age and setting (e.g. schools). Manna et al. extended these matrices to include income and educational attainment. Instead of a traditional contract matrix of C_{ij} where i and j represent different age brackets, Manna et al. transformed the contract matrix into G_{ab} where a and b are combinations of subgroups (e.g. 18–35 years, high-income, and highly educated individuals in contact with 35–55 years, middle-income, and minimally educated individuals). Their work demonstrates that ignoring socioeconomic variables can underestimate the basic reproductive number (Manna et al., 2024).

4.4. Limitations

There are limitations to the Delphi methodology. There is an inherent researcher and subject bias given the purposeful sampling strategy. However, an effort was made to have representation across sex, disciplines, and countries to promote heterogeneity in responses. There is no clear guideline on the ideal number of participating experts, what defines an expert, how many rounds should be completed, and what defines consensus. The methodology for this study followed the most commonly accepted methods, including ≥70 % percent agreement and three survey rounds (Niederberger and Spranger, 2020). Regarding the appropriate number of experts, this study included 22, guided by a recent review recommending 8–23 participants (Shang, 2023). Importantly, while attrition is the norm for Delphi studies, this study had a 100 % response rate. This is meaningful in comparison to an initially large number of participants but low response rate. The method relies on expert opinion rather than statistical and empirical evidence. However, the Delphi method is an established approach to building consensus, especially for practices in health (Niederberger and Spranger, 2020).

4.5. Conclusion

There is potential to further the field. A future extension of building collaborations is investments in communities to build and inform their own models. As it stands, many models about LMICs do not include an LMIC author, with most SV models generated by high-income country (HIC) institutions (Naidoo et al., 2024). While there are many groups working on training local practitioners in modelling, there is still the challenge of “modelling colonizers.” Diversifying those who can model is an important endeavour, especially given the context-specific nature of SV. Second, overarching criticisms of SV’s inclusion in modelling are the extensive resources and time required to build partnerships, collect data, and carefully integrate parameters. Given its demonstrated importance in equitable and effective epidemic resilience, everyone – from modellers to funders – needs to prioritise SV to make these resources available.

The integration of social vulnerability ensures epidemic mathematical models more closely represent the world around us. This context impacts the success of ensuing policy and programmatic interventions and supports equitable epidemic preparedness and response. Given the recent focus on the social determinants of pandemic resilience, this study provides both process and technical recommendations to incorporate SV into epidemic modelling.

CRediT authorship contribution statement

Megan Naidoo: Writing – review & editing, Writing – original draft, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Whitney Shephard:** Writing – review & editing, Writing – original draft, Project administration, Methodology, Formal analysis, Data curation, Conceptualization. **Nokuthula Mtshali:** Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization. **Innocensia Kambewe:** Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization. **Bernedette Muthien:** Writing – review & editing, Investigation, Data curation, Conceptualization. **Nadia N. Abuelezam:** Writing – review & editing, Investigation, Data curation, Conceptualization. **Miguel Ponce-de-Leon:** Writing – review & editing, Investigation, Data curation, Conceptualization. **Daniel A.M. Villela:** Writing – review & editing, Investigation, Data curation, Conceptualization. **Romulo Paes-Sousa:** Writing – review & editing, Investigation, Data curation, Conceptualization. **Wirichada Pan-ngum:** Writing – review & editing, Investigation, Data curation, Conceptualization. **David Dowdy:** Writing – review & editing, Investigation, Data curation, Conceptualization. **Stephen S. Morse:** Writing – review & editing, Investigation, Data curation, Conceptualization. **Daiana Pena:** Writing – review & editing, Investigation, Data curation, Conceptualization. **Lorena G. Barberia:** Writing – review & editing, Investigation, Data curation, Conceptualization. **Rein M.G.J. Houben:** Writing – review & editing, Investigation, Data curation, Conceptualization. **Pedro Arcos González:** Writing – review & editing, Investigation, Data curation, Conceptualization. **Jamela E. Robertson:** Writing – review & editing, Investigation, Data curation, Conceptualization. **Rachid Muleia:** Writing – review & editing, Investigation, Data curation, Conceptualization. **Olanrewaju Lawal:** Writing – review & editing, Investigation, Data curation, Conceptualization. **Davide Rasella:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Formal analysis, Data curation, Conceptualization.

Ethics approval

The Research Ethics Committee of the Hospital Clínic de Barcelona granted an exemption from ethics approval as participants were professional experts providing guidance.

Acknowledgements

The project that gave rise to these results received the support of a fellowship from the “la Caixa” Foundation (ID 100010434). The fellowship code is LCF/BQ/DI21/11860050. MN is the principal awardee. The Barcelona Institute for Global Health and DR acknowledge support from the grant CEX2023-0001290-S funded by MCIN/AEI/10.13039/501100011033, and support from the Generalitat de Catalunya through the CERCA Program. The sponsors did not have a role in the study design, collection, analysis and interpretation of data, writing of the report, or decision to submit the article for publication. The authors thank all the participants for their time and expertise.

Appendix A. Participants’ characteristics

Participant characteristic	n	%
Gender		
Man	13	59.1 %
Woman	9	40.9 %
Non-binary or gender non-conforming	0	0.0 %
Country of origin		
South Africa	5	22.7 %
Brazil	4	18.2 %
United States of America	4	18.2 %
Ghana	1	4.5 %
Greece	1	4.5 %
Mozambique	1	4.5 %
Netherlands	1	4.5 %
Nigeria	1	4.5 %
Spain	1	4.5 %
Thailand	1	4.5 %

(*continued on next page*)

(*continued*)

Participant characteristic	n	%
United States of America/Mexico	1	4.5 %
Uruguay/Italy	1	4.5 %
Number of years of experience		
20+	13	59.1 %
10-14	7	31.8 %
15-19	2	9.1 %
Area(s) of expertise *		
Epidemiology	14	19.7 %
Modelling	11	15.5 %
Infectious diseases	10	14.1 %
Outbreaks, epidemics, or pandemics	9	12.7 %
Policy	7	9.9 %
Social sciences	6	8.5 %
Community health	4	5.6 %
Data provider or collector	3	4.2 %
Healthcare or medical field	2	2.8 %
Anthropology	1	1.4 %
Bioethics	1	1.4 %
Global health justice	1	1.4 %
Governance and management science	1	1.4 %
Philosophy	1	1.4 %

* Values will not equal 100 as participants could select more than one area of expertise.

Appendix B. Indicators of social vulnerability to epidemics

Table 1
Thematic list of social vulnerabilities to epidemics

Theme	n	%
Living conditions	54	23.7
Health	46	20.2
Demographics	31	13.6
Income	31	13.6
Vulnerable populations	14	6.1
Education	10	4.4
Knowledge, attitudes, and practices, and culture	9	3.9
Technology and information	7	3.1
Social protection	6	2.6
Social discrimination and structural injustice	5	2.2
Outbreak-specific	4	1.8
Other	11	4.8
GRAND TOTAL	**228**	**100.0**

Table 2
Detailed list of social vulnerability indicators to epidemics

Indicator (N = 228)	n	%*
Living conditions (n = 54)		
Access to sanitation	14	25.9
Household density and composition	12	22.2
Access to clean water	10	18.5
Living conditions and housing quality	5	9.3
Access to electricity	3	5.6
Geographic location	3	5.6
Type of neighbourhood (urban, rural, informal settlement, farm)	3	5.6
Home ownership	1	1.9
Living style	1	1.9
Storage facility to store food adequately	1	1.9
Ventilation	1	1.9
Health (n = 46)		
Access to care (n=20)		
Access to healthcare	12	60.0
Vaccination coverage	3	15.0
Access and cost of private care	1	5.0
Access to primary healthcare	1	5.0
Access to antenatal care	1	5.0
Access to psychosocial support	1	5.0

(*continued on next page*)

Table 2 (*continued*)

Indicator (N = 228)	n	%*
Distance from household to a healthcare unit	1	5.0
Health status (n=16)		
Disability status	4	25.0
Pregnancy status	2	12.5
Chronic disease status	1	6.3
General health status of households	1	6.3
Genetic predisposition to disease	1	6.3
Maternal mortality	1	6.3
Morbidity rates	1	6.3
Newborn mortality rates	1	6.3
Pre-existing health conditions	1	6.3
Sexually transmitted infections	1	6.3
Under 1 mortality rates	1	6.3
Under 5 mortality rates	1	6.3
Nutritional status (n=8)		
Access to healthy foods	3	37.5
Nutritional status	3	37.5
Body Mass Index	1	12.5
Nutrition education	1	12.5
Substance use (n=2)		
Alcohol addictive disorder	1	50.0
Smoking status	1	50.0
Demographics (n = 31)		
Sex and gender	11	35.5
Age	10	32.3
Race and ethnicity	7	22.6
Language	2	6.5
Birth order	1	3.2
Income (n = 31)		
Income-level	8	25.8
Poverty	6	19.4
Employment status	4	12.9
Socioeconomic status	3	9.7
Earnings of pensioners in the household	2	6.5
Type of work (informal, formal, etc.)	2	6.5
Working conditions	2	6.5
Access to financial resources	1	3.2
Multidimensional poverty index	1	3.2
Personal debt	1	3.2
Sick leave	1	3.2
Vulnerable populations (n = 14)		
Migrant status (undocumented, refugee etc.)	8	57.1
Current or previously incarcerated	3	21.4
Homelessness	1	7.1
Indigenous	1	7.1
Marginalised status	1	7.1
Education (n = 10)		
Education level	6	60.0
Literacy	4	40.0
Knowledge, attitudes, and practices, and culture (n = 9)		
Cultural and religious beliefs	3	33.3
Community structure (clan-based, religious leaders, etc)	1	11.1
Conscience	1	11.1
Ideology of household members	1	11.1
Social capital	1	11.1
Social cohesion	1	11.1
Trust in government and public institutions	1	11.1
Technology and information (n = 7)		
Access to information from reliable sources	5	71.4
Access to internet	1	14.3
Ownership of a cell phone	1	14.3
Social protection (n = 6)		
Access to social assistance programmes (e.g. cash assistance)	2	33.3
Insurance status	1	16.7
Reliance on public transportation by type	1	16.7
Shelter access	1	16.7
Welfare state	1	16.7
Social discrimination and structural injustice (n = 5)		
Discrimination	1	20.0
Exposure to structural stress	1	20.0
Exposure to racism	1	20.0
Lack of access to services due to historical deprivation	1	20.0
Social standing	1	20.0
Outbreak-specific (n = 4)		
Access to personal protective equipment	1	25.0
Epidemiologic information on previous outbreaks	1	25.0

(*continued on next page*)

Table 2 (*continued*)

Indicator (N = 228)	n	%*
Organised health programs for combating endemic infectious diseases	1	25.0
Organised health surveillance and laboratory networks	1	25.0
Other (n = 11)		
Crime (homicide and armed robbery)	2	18.2
Water, air, and land pollution	2	18.2
Childcare status	1	9.1
Conflict and war	1	9.1
Cost of minimum food and medicines basket	1	9.1
Human Development Index	1	9.1
National and local commitments to international treaties and recommendations	1	9.1
Number of daily contacts	1	9.1
Number of extreme events (floods, droughts, storms)	1	9.1

* Values may not equal 100 % due to rounding.

Data availability

Data will be made available on request.

References

Abuelezam, N.N., Michel, I., Marshall, B.D., et al., 2023. Accounting for historical injustices in mathematical models of infectious disease transmission: an analytic overview. Epidemics 43, 100679. https://doi.org/10.1016/j.epidem.2023.100679.

Ali, S., Li, Z., Moqueet, N., et al., 2024. Incorporating social determinants of health in infectious disease models: a systematic review of guidelines. Med. Decis. Mak. 44 (7), 742–755. https://doi.org/10.1177/0272989X241280611.

Andradóttir, S., Chiu, W., Goldsman, D., Lee, M.L., 2014. Simulation of influenza propagation: model development, parameter estimation, and mitigation strategies. IIE Trans. Healthc. Syst. Eng. 4 (1), 27–48. https://doi.org/10.1080/19488300.2014.880093.

Bambra, C., 2022. Pandemic inequalities: emerging infectious diseases and health equity. Int. J. Equity Health 21, 6. https://doi.org/10.1186/s12939-021-01611-2.

Bambra, C., Riordan, R., Ford, J., et al., 2020. The COVID-19 pandemic and health inequalities. J. Epidemiol. Community Health 174, 964–968. https://doi.org/10.1136/jech-2020-214401.

Banerjee, S., 2019. Towards a quantitative model of epidemics during conflicts. Interdiscip. Descr. Complex Syst. 17, 598–614. https://doi.org/10.7906/indecs.17.3.16.

Bargain, O., Aminjonov, U., 2020. Between a Rock and a Hard Place: Poverty and COVID-19 in Developing Countries. Institute of Labor Economics (IZA). Available from: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3614245.

Bartoletti, M., Bussini, L., Bavaro, D.F., et al., 2024. What do clinicians mean by epidemics' preparedness. Clin. Microbiol. Infect. 30 (5), 586–591. https://doi.org/10.1016/j.cmi.2023.05.030.

Basu, S., Andrews, J., 2013. Complexity in mathematical models of public health policies: a guide for consumers of models. PLoS Med. 10 (10), e1001540. https://doi.org/10.1371/journal.pmed.1001540.

Bedson, J., Skrip, L.A., Pedi, D., et al., 2021. A review and agenda for integrated disease models including social and behavioural factors. Nat. Hum. Behav. 5, 834–846. https://doi.org/10.1038/s41562-021-01136-2.

Behrend, M.R., Basáñez, M.G., Hamley, J.I.D., et al., 2020. Modelling for policy: the five principles of the neglected tropical diseases modelling consortium. PLoS Neglected Trop. Dis. 14 (4), e0008033. https://doi.org/10.1371/journal.pntd.0008033. Published 2020 Apr 9.

Bernoulli, D., 1760. Essai d'une nouvelle analyse de la mortalité causée par la petite vérole et des advantages de l'inoculation pour la préventir. Mém Math Phys Acad Roy Sci Paris 1–45.

Bershteyn, A., Kim, H.Y., Braithwaite, R.S., 2022. Real-time infectious disease modeling to inform emergency public health decision making. Annu. Rev. Publ. Health 43, 397–418. https://doi.org/10.1146/annurev-publhealth-052220-093319.

Buckee, C., Noor, A., Sattenspiel, L., 2021. Thinking clearly about social aspects of infectious disease transmission. Nature 595. https://doi.org/10.1038/s41586-021-03694-x.

Caro, J.J., Briggs, A.H., Siebert, U., et al., 2012. Modeling good research practices - overview: a report of the ISPOR-SMDM modeling good research practices task force-1. Value Health 15 (6), 796–803.

Chang, S., Pierson, E., Koh, P.W., et al., 2021. Mobility network models of COVID-19 explain inequities and inform reopening. Nature 589, 82–87. https://doi.org/10.1038/s41586-020-2923-3.

Cutter, S.L., Finch, C., 2008. Temporal and spatial changes in social vulnerability to natural hazards. Environ. Sci. 105 (7), 2301–2306. https://doi.org/10.1073/pnas.0710375105.

Dasgupta, S., Bowen, V.B., Leidner, A., et al., 2020. Association between social vulnerability and a County's risk for becoming a COVID-19 hotspot - united States, June 1-July 25, 2020. MMWR Morb. Mortal. Wkly. Rep. 69 (42), 1535–1541. https://doi.org/10.15585/mmwr.mm6942a3.

de Boer, R., Lutscher, F., 2018. Choice disability as a target for non-medical HIV intervention. Math. Biosci. 299, 127–137. https://doi.org/10.1016/j.mbs.2018.03.015.

Diekmann, O., Heesterbeek, H., Britton, T., 2012. Mathematical Tools for Understanding Infectious Disease Dynamics. Princeton University Press. https://doi.org/10.1515/9781400845620.

Durante, R., Guiso, L., Gulino, G., 2021. Asocial capital: civic culture and social distancing during COVID-19. J. Publ. Econ. 194, 104–342. https://doi.org/10.1016/j.jpubeco.2020.104342.

Epstein, J.M., Parker, J., Cummings, D., Hammond, R.A., 2008. Coupled contagion dynamics of fear and disease: mathematical and computational explorations. PLoS One 3 (12), e3955. https://doi.org/10.1371/journal.pone.0003955.

Flanagan, B.E., Gregory, E.W., Hallisey, E.J., et al., 2011. A social vulnerability index for disaster management. J. Homel. Secur. Emerg. Manag. 8. https://doi.org/10.2202/1547-7355.1792.

Funk, S., Bansal, S., Bauch, C.T., et al., 2015. Nine challenges in incorporating the dynamics of behaviour in infectious diseases models. Epidemics 10.

Galanis, G., Hanieh, A., 2021. Incorporating social determinants of health into modelling of COVID-19 and other infectious diseases: a baseline socio-economic compartmental model. Soc. Sci. Med. 274, 113794. https://doi.org/10.1016/j.socscimed.2021.113794.

GBD 2021 Demographics Collaborators, 2024. Global age-sex-specific mortality, life expectancy, and population estimates in 204 countries and territories and 811 subnational locations, 1950-2021, and the impact of the COVID-19 pandemic: a comprehensive demographic analysis for the global burden of disease study 2021. Lancet 403, 1989–2056. https://doi.org/10.1016/S0140-6736(24)00476-8, 10440.

Grant, C., Lo Iacono, G., Dzingirai, V., et al., 2016. Moving interdisciplinary science forward: integrating participatory modelling with mathematical modelling of zoonotic disease in Africa. Infect. Dis. Poverty 5, 17. https://doi.org/10.1186/s40249-016-0110-4.

Humphrey-Murto, S., Varpio, L., Wood, T.J., et al., 2017. The use of the Delphi and other consensus group methods in medical education research: a review. Acad. Med. 92, 1491–1498. https://doi.org/10.1097/ACM.0000000000001812.

Jit, M., Brisson, M., 2011. Modelling the epidemiology of infectious diseases for decision analysis: a primer. Pharmacoeconomics 29 (5), 371–386. https://doi.org/10.2165/11539960-000000000-00000.

Kantamneni, N., 2020. The impact of the COVID-19 pandemic on marginalized populations in the United States: a research agenda. J. Vocat. Behav. 119. https://doi.org/10.1016/j.jvb.2020.103439.

Kermack, W.O., McKendrick, A.G., 1927. A contribution to the mathematical theory of epidemics. Proc R Soc Lond Series A 115 (772), 700–721.

Kretzschmar, M.E., Ashby, B., Fearon, E., et al., 2022. Challenges for modelling interventions for future pandemics. Epidemics 38, 100546. https://doi.org/10.1016/j.epidem.2022.100546.

Laird, Y., Manner, J., Baldwin, L., Hunter, R., McAteer, J., Rodgers, S., Williamson, C., Jepson, R., 2020. Stakeholders' experiences of the public health research process: time to change the system? Health Res. Pol. Syst. 18 (1), 83. https://doi.org/10.1186/s12961-020-00599-5.

Li, H., Wang, W., 2022. Knowledge domain and emerging trends of social vulnerability research: a bibliometric analysis (1991-2021). Int. J. Environ. Res. Publ. Health 19 (14), 8342. https://doi.org/10.3390/ijerph19148342.

Linstone, H.A., Turoff, M., 1975. The Delphi Method: Techniques and Application. Addison-Wesley. https://doi.org/10.2307/3150755.

Livingston, E., Desai, A., Berkwits, M., 2020. Sourcing personal protective equipment during the COVID-19 pandemic. JAMA 323 (19), 1912–1914. https://doi.org/10.1001/jama.2020.5317.

Mah, J.C., Penwarden, J.L., Pott, H., et al., 2023. Social vulnerability indices: a scoping review. BMC Public Health 23, 1253. https://doi.org/10.1186/s12889-023-16097-6.

Manna, A., Dall'Amico, L., Tizzoni, M., Karsai, M., Perra, N., 2024. Generalized contact matrices allow integrating socioeconomic variables into epidemic models. Sci. Adv. https://doi.org/10.1126/sciadv.adk4606.

Mirugwe, A., Ashaba, C., Namale, A., et al., 2024. Sentiment analysis of social media data on ebola outbreak using deep learning classifiers. Life 14 (6), 708. https://doi.org/10.3390/life14060708.

Moran, E., Kubale, J., Noppert, G., et al., 2020. Inequality in acute respiratory infection outcomes in the United States: a review of the literature and its implications for public health policy and practice. medRxiv. https://doi.org/10.1101/2020.04.22.20069781.
Mubangizi, J.C., 2021. Poor lives matter: COVID-19 and the plight of vulnerable groups with specific reference to poverty and inequality in South Africa. J. Afr. Law 65 (S2), 237–258. https://doi.org/10.1017/S0021855321000292.
Naidoo, M., Shephard, W., Kambewe, I., et al., 2024. Incorporating social vulnerability in infectious disease mathematical modelling: a scoping review. BMC Med. 22 (1), 125. https://doi.org/10.1186/s12916-024-03333-y. Published 2024 Mar 18.
Nande, A., Sheen, J., Walters, E.L., et al., 2021. The effect of eviction moratoria on the transmission of SARS-CoV-2. Nat. Commun. 12, 2274. https://doi.org/10.1038/s41467-021-22521-5.
Neiderud, C.J., 2015. How urbanization affects the epidemiology of emerging infectious diseases. Infect. Ecol. Epidemiol. 5, 27060. https://doi.org/10.3402/iee.v5.27060. Published 2015 Jun 24.
Niederberger, M., Spranger, J., 2020. Delphi technique in health sciences: a map. Front. Public Health 8. https://doi.org/10.3389/fpubh.2020.00457.
Niu, Y., Li, Z., Meng, L., Wang, S., Zhao, Z., Song, T., Lu, J., Chen, T., Li, Q., Zou, X., 2021. The collaboration between infectious disease modeling and public health decision-making based on the COVID-19. J. Saf. Sci. Resilience 2 (2), 69–76. https://doi.org/10.1016/j.jnlssr.2021.06.001.
Pollett, S., Johansson, M.A., Reich, N.G., et al., 2023. Recommended reporting items for epidemic forecasting and prediction research: the EPIFORGE 2020 guidelines [published correction appears in PLoS Med PLoS Med. 20 (11), e1004316. https://doi.org/10.1371/journal.pmed.1004316, 2021;18(10):e1003793. Published 2021 Oct 19. doi:10.1371/journal.pmed.1003793.
Ran, J., MacGillivray, B.H., Gong, Y., Hales, T.C., 2020. The application of frameworks for measuring social vulnerability and resilience to geophysical hazards within developing countries: a systematic review and narrative synthesis. Sci. Total Environ. 711, 134486. https://doi.org/10.1016/j.scitotenv.2019.134486.
Richard, D.M., Lipsitch, M., 2024. What's next: using infectious disease mathematical modelling to address health disparities. Int. J. Epidemiol. 53, 1. https://doi.org/10.1093/ije/dyad180.
Sierra, M., Franco-Paredes, C., Agudelo Higuita, N.I., 2023. Health inequities in the global response to the COVID-19 pandemic. Ther. Adv. Infect. Dis. 10, 20499361231162726. https://doi.org/10.1177/20499361231162726. Published 2023 Apr 10.
Shang, Z., 2023. Use of Delphi in health sciences research: a narrative review. Medicine (Baltim.) 102 (7), e32829. https://doi.org/10.1097/MD.0000000000032829. PMID: 36800594; PMCID: PMC9936053.
Skrip, L.A., Fallah, M.P., Bedson, J., Hébert-Dufresne, L., Althouse, B.M., 2021. Coordinated support for local action: modeling strategies to facilitate behavior adoption in urban-poor communities of Liberia for sustained COVID-19 suppression. Epidemics 37, 100529. https://doi.org/10.1016/j.epidem.2021.100529.
Staniszewska, S., Hill, E.M., Grant, R., et al., 2021. Developing a framework for public involvement in mathematical and economic modelling: bringing new dynamism to vaccination policy recommendations. Patient 14 (4), 435–445. https://doi.org/10.1007/s40271-020-00476-x [published correction appears in Patient. 2021 Jul;14 (4):447. doi: 10.1007/s40271-021-00497-0].
Stanturf, J.A., Goodrick, S.L., Warren Jr., M.L., Charnley, S., Stegall, C.M., 2015. Social vulnerability and ebola virus disease in rural Liberia. PLoS One 10 (9), e0137208. https://doi.org/10.1371/journal.pone.0137208. Published 2015 Sep. 1.
Sumibcay, J.R.C., Kunichoff, D., Bassett, M.T., 2024. Racial and ethnic disparities in COVID-19 mortality. JAMA Netw. Open 7 (5), e2411656. https://doi.org/10.1001/jamanetworkopen.2024.11656. Published 2024 May 1.
Sweileh, W.M., 2022. Global research activity on mathematical modeling of transmission and control of 23 selected infectious disease outbreak. Glob. Health 18 (1), 4. https://doi.org/10.1186/s12992-022-00803-x.
Thangaratinam, S., Redman, C.W.E., 2005. The Delphi technique. Obstet. Gynaecol. 7, 120–125. https://doi.org/10.1576/toag.7.2.120.27071.
Thomas, D.R., 2006. A general inductive approach for analyzing qualitative evaluation data. Am. J. Eval. 27 (2), 237–246. https://doi.org/10.1177/1098214005283748.
Tizzoni, M., Nsoesie, E.O., Gauvin, L., et al., 2022. Addressing the socioeconomic divide in computational modeling for infectious diseases. Nat. Commun. 13, 2897. https://doi.org/10.1038/s41467-022-30688-8.
Torres, I., Thapa, B., Robbins, G., et al., 2021. Data sources for understanding the social determinants of health: examples from two middle-income countries: the 3-D commission. J. Urban Health 98 (Suppl. 1), 31–40. https://doi.org/10.1007/s11524-021-00558-7.
Wardle, J., Bhatia, S., Kraemer, M.U.G., Nouvellet, P., Cori, A., 2023. Gaps in mobility data and implications for modelling epidemic spread: a scoping review and simulation study. Epidemics 42, 100666. https://doi.org/10.1016/j.epidem.2023.100666.
White, P.J., 2017. Mathematical models in infectious disease epidemiology. Infectious Diseases 49–53.e1. https://doi.org/10.1016/B978-0-7020-6285-8.00005-8.
Williams, T.G., Brown, D.G., Guikema, S.D., et al., 2022. Integrating equity considerations into agent-based modeling: a conceptual framework and practical guidance. J. Artif. Soc. Soc. Simulat. 25 (3). https://doi.org/10.18564/jasss.4816.
World Health Organisation, 2008. Closing the Gap in a Generation. https://iris.who.int/bitstream/handle/10665/69832/WHO_IER_CSDH_08.1_eng.pdf?sequence=1. (Accessed 29 November 2024).
Zelner, J., Masters, N.B., Naraharisetti, R., et al., 2022. There are no equal opportunity infectors: epidemiological modelers must rethink our approach to inequality in infection risk. PLoS Comput. Biol. 18 (2), e1009795. https://doi.org/10.1371/journal.pcbi.1009795.