UK Inquiry collection: four key questions to consider for the role of mathematical modelling in future pandemic response policy

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Mathematical modelling is a crucial contributor to any country's pandemic response, but its usefulness can be hindered by lack of interdisciplinarity, lack of data sharing, poor or absent communication, and modelling over unrealistically long timeframes.

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Introduction

The UK Inquiry into the Covid-19 pandemic published its draft terms of reference in March 2022 (1). Part of the aims of the Inquiry is to examine how decisions were made and communicated; intergovernmental decision-making and the availability and use of data and evidence. Mathematical modelling underpinned much of the advice that the Scientific Advisory Group for Emergencies (SAGE) (and others) provided to government and as such should be a focus of the Inquiry.

The Scientific Pandemic Influenza Group on Modelling (SPI-M) gives expert advice to the Department of Health and Social Care and wider UK government on emerging human infectious disease threats. During the pandemic, SPI-M has reported to SAGE. The membership of the group is drawn from a range of UK institutions and their advice is based on infectious disease modelling and epidemiology. A detailed review of how SPI-M feeds into policy via SAGE was published in 2021 (2). Its modelling has been influential throughout, particularly during the first eighteen months of the pandemic.

For instance, the Imperial College "Report 9" (3) was an important trigger which pushed the UK government to implement a lockdown in March 2020. The same modelling group later suggested that delays in taking action cost tens of thousands of lives in the UK (4). In July 2020, modelling was used to project the number of deaths that might have been expected over the winter of 2020/2021 in a reasonable worst-case scenario. The prediction, at the time largely reported as being overly fatalistic (5), was of 85,000 deaths between July 2020 and March 2021 (6). In actuality, between 1 July 2020 and 31 March 2021 almost 100,000 deaths with Covid-19 on the death certificate were recorded in the UK (7). Projections from multiple independent modelling teams informed the UK's "Roadmap" (8) for release from lockdown in February 2021 and implementation of "Plan B" measures in December 2021 (9). Modelling (10) determined the vaccine priority groups in December 2020, which played a significant role in the UK's successful vaccine rollout and consequently saving thousands of lives over the first half of 2021. SPI-M's work has also been important in evaluating the relative impact of different interventions, such as the importance of home working in reducing transmission in 2021 (11).

Throughout the pandemic, official modelling efforts have been subjected to criticism from many different quarters. No doubt some of that criticism has been understandable – a result of highly publicised projections that never came to pass. Some of these missteps have derived directly from failures of the modelling process to capture reality – mistakes in model parameterisation from uncertain data, misunderstanding or misinterpretation of the key features of the situations being modelled and a fundamental inability to capture important facets of human behaviour. However, much of the criticism modellers have received has been misplaced, a result of fundamental misunderstandings of the purpose of mathematical modelling, what it is capable of – and how its results should be interpreted. In turn, the misunderstandings result, in part, from failures in communication.

This has been seen most recently in sustained criticism of SPI-M models on the impact of Omicron in the UK in December 2021 (12–16). The models turned out to be too pessimistic due to a combination of uncertainty about Omicron's severity and uncertainty about how the public would react to growing cases. In the end, Omicron proved to be somewhat less severe than Delta, the boosters more effective, and - for the first Omicron wave - the public voluntarily restricted their contacts and took up rapid antigen testing much more than expected, which all combined to reduce the wave's severity (17–19). The model assumptions were clear within the reports (20–22), but the attacks expanded to cover the whole of SPI-M's contribution (23,24). However, what was not anticipated in the modelling, or in policy, was a second (and just as large) Omicron wave just three months after the first. In fact, the combined stress of two waves in short succession contributed to the worst waits for emergency care (25) since data collection began and high levels of sick leave in the NHS (26).

In this paper, we cover briefly how epidemiological modelling can be used to inform policy before posing four key questions for the upcoming UK Inquiry around the role of mathematical modelling in supporting policy. Firstly, where can greater interdisciplinarity improve the usefulness of models? Secondly, how can data be generated and shared more within and between different modelling groups to sustain a more egalitarian and robust modelling environment? Thirdly, would better public communication of modelling processes as well as the underlying assumptions improve usefulness of the models, and if so, how can this be supported? Fourthly, how helpful were pandemic projections looking a year or more ahead?

We note that SAGE were not charged with the economic modelling of policy options and that this is beyond the remit of this paper. The Inquiry might like to separately consider whether and how economic modelling could have been part of the SAGE remit.

How mathematical modelling is used to inform policy

Mathematical modelling provides a framework in which we can formalise our assumptions about the processes we are trying to capture (e.g. disease spread and impact), build them into a simplified representation of reality and simulate forwards in time in order to suggest what might happen in the future under different policy options (27,28). Modelling is also extremely useful in understanding the underlying situation where we have incomplete or missing data (29,30), and indeed can shed light on what has happened in the past where the picture is murky, such as the impact of different public health mitigations (29). A detailed review of how SPI-M was formed and how its work feeds into government policy via SAGE was published in 2021 (2).

Epidemiological modelling is much more akin to science than it is to pure mathematics. The process involves iteratively building models, making predictions, comparing these predictions to observations, and then refining the models. Through this repetitive process modellers can build accurate, detailed, and robust representations of reality, which can then be used to speculate what will happen in hitherto unseen scenarios. Most applications of mathematical modelling allow for many repeats of this cycle over periods of weeks, months or even years. In contrast, synthesising appropriate data to populate and fine-tune models in real time during an epidemic is an almost unique challenge in applied mathematics and one which only a few mathematicians ever experience (2).

Any modelling comes with various uncertainties and assumptions that need to be thought through, examined and explained (31). Significant errors in any area can derail the usefulness of the model, and, if not understood and recognised, cause harm. In the context of a rapidly evolving pandemic this is even more important. Good mathematical modelling must be transparent about all the sources of uncertainty (Figure 1) and provide sufficient detail to outsiders (including policymakers) to assess the model outputs.

SPI-M modelling has been admirably transparent about key assumptions and parameter estimates and have typically encompassed a range of scenarios. They have incorporated inherent variability and caveated many of the problems associated with unknown future events. Structural details of the SPI-M modelling are usually available in academic papers but are not easily accessible to a non-academic audience. Nonetheless, these efforts have not been sufficient to prevent mistakes or criticism. What then are key questions around the role of modelling that the Inquiry should address?

Questions for the Inquiry

Q1. Who was invited to contribute to the design of the models and estimation of the parameters?

As described above, model building is iterative. The structure of the model and its input parameters are continuously refined in light of the latest evidence and understanding about the dynamics of the disease and its spread. Perhaps the biggest threat to the usefulness of the models appears when important information/knowledge relating to the dynamics is held by experts who are not connected to the modelling community. The modelling of care homes during the Covid-19 pandemic represents perhaps the most important cautionary tale.

It was known early on that older and sicker populations were at much higher risk of severe illness and death from Covid-19. Modellers on SPI-M quickly understood that the elderly, and particularly those in care-homes were at significant risk should they catch coronavirus. The need for protection of care home residents was also well appreciated, yet surprisingly care homes only appear twice (32) in the minutes of the Scientific Advisory Group for Emergencies (SAGE) during the first five months of the pandemic. Modellers had extensive access to excellent hospital surveillance data set up rapidly at the start of the pandemic (33), but the domain specific knowledge allowing models of social care settings to be appropriately represented and thereby care-homes to be properly protected was not well understood. The intersecting factors of an extremely vulnerable population living in shared accommodation, frequent contact with friends and relatives in the community, the discharge of potentially sick patients from hospitals, lack of personal protective equipment and low-paid staff (with little access to sick pay, working across multiple homes as agency workers and more likely to live in multi-occupancy poor housing) were all identified by industry practitioners as particular system vulnerabilities. Many of these issues, however, did not seem to be anticipated or explicitly taken into account by the modellers.

While it is not reasonable to expect mathematical modellers to have a prior understanding of the details of the social care sector and the interacting features of vulnerable populations and staff, it is reasonable to expect that modellers should anticipate there may be important unknown factors on which they should canvas domain-specific expertise. To domain experts, the vulnerabilities in the system were both knowable and known. The apparent shortfall on the part of the modellers was in not realising that there was a knowledge gap and subsequently failing to identify and gain knowledge from those with the requisite expertise. Once the vulnerability of care homes became clearer to modellers, their specific features were successfully incorporated into models which then (albeit with hindsight) highlighted the high numbers of deaths if mitigations were not adequate. In England and Wales there were more than 27,000 deaths in care homes during the first wave of the pandemic.

Government-convened modelling subgroups should incorporate as much diverse expertise as possible – an aspect also considered by the Parliamentary Committee on Science and Technology (34). Learning could be drawn from published literature on interdisciplinary working (35) in disaster response (36–38) and adapted to the UK situation. The mechanisms for ensuring interdisciplinary working must be in place and documented before a pandemic hits and should be agnostic to the nature of the pandemic or to the lead experts at the time: that is, incorporating other perspectives should not depend on the experience or personal network of the expert leads. This recommendation in fact goes beyond the role of modelling in the UK response and applies to the overall structure of SAGE with its relatively siloed working groups feeding independently into decision making.

Q2. Could data have been shared more widely?

The information used to build, refine and characterise models of infectious disease might include raw data on the spread of the disease (e.g. case numbers, hospitalisation numbers, deaths etc), data on the parameters which feed into models (e.g. transmissibility, severity, incubation period, etc) assumptions underlying model structure (e.g. is there a significant pre-infectious “exposed period” etc) and the outputs of models (e.g. predictions of case numbers, hospitalisations etc). Retrospectively, a problem with data accessibility (particularly the raw data and parameterisation data) within SPI-M was identified by some of its members. Some groups had access to better quality data that was not shared with all modelling groups. It was regarded by the chair of SPI-M that these disparities in data availability were “inevitable” and that some groups would necessarily have a “head start” because of the effort they had put in to create those networks through which the data was being shared (39). As a result of the paucity of available data, some researchers on SPI-M were forced to resort to dredging Wikipedia early on in the pandemic, citing the fact it was the only data stream that was publicly available at the time (40). Some modellers described the data that was publicly available as being of extremely poor quality. Initially, there was only limited data sharing across countries – reducing the learning possible from others' earlier experience. The importance of international data sharing has been shown repeatedly via, for example, the genomic data on new variants disseminated via GISAID (41).

It is possible that the initial lack of data sharing contributed to mistakes made early on in the pandemic. Groups with access to poorer quality data did not feel able to challenge the conclusions of groups with access to better quality data. There have been stark examples of situations in which this data disparity has led to poor modelling outcomes. In March 2020 the doubling time in the UK epidemic was overestimated by SPI-M. Estimates of a doubling time of 5-7 days made their way to SAGE (42) and thence to policymakers. The true doubling time was more likely to be around three days. As a result of the incorrect doubling time, Patrick Vallance would claim we were "maybe four weeks or so behind [Italy] in terms of the scale of the outbreak" when in fact the UK was more like two weeks behind (43). This incorrect calculation may have provided a false sense of security which in turn might have contributed to the UK's disastrous delay in taking measures to suppress the epidemic (44), which resulted in the avoidable loss of tens of thousands of lives (45,46).

SPI-M have since instituted better methods of model-averaging, which have been used, for example, to come up with consensus views on estimates of the reproduction number and growth rates of the disease. However, it is not clear that issues pertaining to the sharing of other data sources required to construct effective models have been resolved (for instance individual-level data on infections, hospitalisations, and deaths; international data). More comprehensive and timely sharing of other data sources might reduce uncertainty and increase accuracy in models, improving their usefulness. A range of better parameterised, but structurally different, models would additionally reduce the impact of structural uncertainty (Fig 1).

Q3. Who should have been responsible for communicating the modelling and resourcing its communication?

Open and clear communication of the outputs of disease transmission models (and indeed the entire modelling process) is vital in supporting policymaker decisions and in increasing the public's understanding of, and desire to abide by, rules that are informed by such models. Indeed, one of the main critiques surrounding mathematical modelling during the pandemic has been the lack of clear and consistent communication (47). Unfortunately, outputs of complex models do not speak for themselves - they need to be explained. This does not necessarily mean that modellers should advocate for specific policies, but they do need to explain what the models can and can't be used for, and why. Some SPI-M scientists recognised the importance of public communication, but reasonably explained that they did not themselves have the time to engage fully, given that their energies were devoted to refining and running models (34).

As a simple example, the inability to correctly recognise and interpret exponential growth, has been shown to act as a significant impediment to the ability of governments to implement effective strategies to control infectious disease (48). The lower the levels of understanding of exponential growth, the lower the levels of compliance with anti-covid measures, including the use of face coverings and social distancing. People who find it hard to accurately estimate the speed of disease spread also find it difficult to see the importance of disease control mitigations and are less likely to implement or observe them. When people better understand the true rate of growth of the epidemic their perception of risk is adjusted accordingly, and they are more likely to comply with suggested protective behaviours.

That said, communication must also involve listening – and different people listen differently and from different perspectives. Smith and Stewart (49) highlight that modelling results may be seized upon by policymakers to support pre-existing policy-goals – a kind of policy-based evidence selection rather than true evidence-based policy. They present further evidence that policy actors may not engage with or understand the process underlying the modelling results they choose to base policy on. Indeed, it may be the case that, in the eyes of policymakers, the complexity of the modelling process provides the model outputs with an 'illusion of certainty', rendering the results difficult to question (50). Excellent communication is necessary but not sufficient for models to appropriately inform policy.

Pandemic policy making differs significantly from normal-time policy making in a number of ways. Firstly, the short timescale over which policies must be determined leaves less time for a proper assessment of the available evidence, adding uncertainty to the modelling and making it hard to communicate the nuances behind modelling results to policymakers. Conversely, the high visibility of much of the scientific evidence during the covid pandemic may have meant policymakers felt under increased scrutiny and under greater pressure therefore to make evidence-based decisions on as a result of this greater public accountability.

Another challenge is that the lack of context surrounding model results means they are open to misinterpretation by the media or exploitation by bad-faith actors. As discussed above, uncertainties in key parameter values and variability mean that good modelling practice is to present a range of different scenarios for different combinations of parameter values alongside prediction intervals which can help to express uncertainty. In particular, the development of reasonable worst-case scenarios follows the public health modelling mantra "plan for the worst, but hope for the best". These worst-case scenarios often generate the most startling projections and consequently capture the news headlines. This, particularly if policy action is taken to avoid the worst outcomes, can lead to accusations of doom-mongering and distrust in future model predictions when these scenarios do not then play out in reality.

A third problem presented by inadequate communication surrounding official modelling efforts is that it leaves a media vacuum, which will necessarily be filled by other academic or amateur modelling efforts. While there is certainly room for different modelling perspectives to the SAGE ones, it does mean that those modellers who present their findings in the most media friendly manner tend to dominate the public perception of modelling. For example, just over a week after the Imperial College modelling group published their report 9 (3), a group of modellers at the University of Oxford published their own pre-print (51). Using a simplistic model, they proposed the UK's epidemic has "already led to the accumulation of significant levels of herd immunity". The article was distributed to the media through a third-party PR firm. Unusually for academic papers, the same PR firm was the only contact listed on the preprint.

As a result of their successful media strategy, the “Oxford model” was presented with the same credibility as the Imperial model (52), despite the very different quality of the modelling undertaken. Although many scientists openly challenged the headline results from the Oxford model (53), their voices were largely drowned out in the media furore. Even without the official sanction of peer review, the press surrounding the modelling had the effect of catapulting the authors to a prominent position from which they were able to influence government policy. Their advice, which went directly to the top of government, may have influenced the decision to delay lockdown in the autumn of 2020.

Communication of modelling is challenging at the best of times and made harder in a pandemic. But this does not mean modellers should not try. Ideally, the authoritative voice on the work should come from the modellers themselves. We need to better train modellers to convey the nuances of the model results and their assumptions to a general audience. Modellers cannot and should not try to completely control the media narrative around their work. Rather we are suggesting that models are accompanied by suitable lay summaries and that either the modellers themselves or well-briefed intermediaries actively engage with journalists about their work to reduce the chances of misrepresentation.

The additional work of communication must be adequately resourced. Funding must be available for modelling teams to have the time and access to the expertise to undertake this communication, or else for this communication to be undertaken by domain experts within government (such as the UK Health Security Agency or the Civil Service, both of which employ many excellent modellers) or outsourced to an independent expert body such as the Royal Statistical Society or the Royal Society of Public Health. Expert communication must also be tailored to each audience and use an appropriate amount of detail (often less than modellers might wish). Decision makers too should receive basic training into how mathematical models inform policy, what questions to ask of modellers and what the potential pitfalls are. Making explicit provision for communication is not an optional extra, but a key part of maximising the benefit of modelling to inform policy and minimising the risk of misuse.

Finally, in order to sustain trust, modelling undertaken for the government should be made publicly available as soon as possible so that the results and the underlying assumptions of the models can be appropriately scrutinised. It is also important that modellers – alongside the interdisciplinary team assembled as discussed in Q1 - should have input into the scenarios they choose to model. In particular, they should not feel restricted to model only those scenarios suggested to them by the government, which risks not taking full advantage of the expertise contained within SAGE. We note though, that even if models were communicated perfectly, their utilisation by other parties is not wholly (or often even largely) within the modellers’ control.

Q4. Were modellers asked to project their models too far into the future?

Currently many SPI-M projections extend 4 to 6 months (54) and some projections (55) go up to a year ahead or more. Fundamental shifts in the dynamics of the pandemic within that time frame can render the projections redundant, as we have seen several times for example with the emergence of new variants or with changes in government policy. For instance, the projections in February 2021 (55) that went up to April 2022, assumed no new variants and no vaccine waning. In fact, four new dominant variants have arisen since then (Delta and Omicron BA.1, BA.2 and BA.4/5) and vaccine waning has been an important factor in determining the trajectory of the pandemic and new vaccine policies.

Whilst there should be no prohibition on delivering long-term forecasts of what a pandemic might look like, and while SPI-M have been transparent about the assumptions made (e.g. no new variants emerging), the results of such projections can nonetheless mislead because the likelihood of such fundamental shifts in pandemic dynamics is poorly understood by both policymakers and the public.

The problem in presenting projections over such a long timeframe is that they can instil a false sense of certainty and complacency, because they do not acknowledge the likelihood (which has proven to be high with SARS-CoV-2) of such fundamental changes occurring. Moving to a shorter timeframe might also encourage policymakers to incorporate more uncertainty and anticipated reassessments into their plans and communication.

There are established methods in other disciplines such as Operational Research or Financial Risk Management that can incorporate the risk of rare but potentially momentous events into decision making (e.g. Conditional Value at Risk strategies (56)). One approach would be to incorporate these into the long-term modelling framework. Another approach would be to use a shorter planning horizon for modelling of no longer than four months or so. Such an approach would recognise that it may be better not to provide projections at all under assumptions that are almost certain to be wrong in several months’ time than to provide not just uncertain, but fundamentally inaccurate, projections over a longer timeframe. Of course, there may be modelling scenarios which are unlikely to be impacted by these trajectory-changing events and for which longer timeframes are suitable. Care should be taken to explain why longer projections are likely to be valid and therefore justified in these instances.

Conclusions

Epidemiological modelling is vital to both understanding the current state of the pandemic and also to predicting what might happen in the future under a range of different scenarios. No doubt, modelling has provided valuable input into the policies designed to tackle coronavirus. No more so is this true than the case of the modelling carried out in March 2020, which is widely regarded to have precipitated the lockdown that was introduced a week later. On the other hand, modelling projections have not always influenced policymakers. A prime example is when the government decided not to impose stricter measures in September 2020 despite SAGE’s suggestions that doing so could halt the early exponential growth in cases (57).

We have suggested four key questions for the UK Inquiry to ask about the input of modelling into government Covid policy. We believe that improvement is necessary in each area: designing processes to ensure that appropriate interdisciplinary expertise informs the modelling; committing to sharing data nationally and internationally, enabling more effective collaboration and reducing over-reliance on any one modelling group; investing in supporting clear communication surrounding the key results of, and assumptions underlying, the modelling; recognising the inherent limitation of any model and using shorter timeframes for modelling. We suggest that with better communication, more openness to dialogue with other communities as well as improved data sharing, epidemiological modelling could more successfully support the UK response to this and future pandemics.

Authors

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Patient and Public Involvement

We have not involved patients or the public in this article, but its content has been informed by extensive public communication during the pandemic across Social, Print and Broadcast Media.

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Sources of uncertainty that affect accuracy of modelling scenarios.

Features of the epidemiological models

Model structure

Does model accurately capture key dynamics of disease spread? e.g.

- age differences
- regional differences
- vaccination differences#
- hospital/school/care home spread
- Symptomatic/asymptomatic spread
- Incubation period

Structure is often refined as more is known about the disease.

Secondly, how does the model capture public behaviour? Current models do not really do this well. Instead, the impact of interventions is often incorporated as blanket reduction in exposure.

Model parameters

This includes estimates of things are measurable but very uncertain early in a pandemic (or a new variant) such as:

- Transmissibility; severity; likelihood of showing symptoms
- Effectiveness of vaccines in preventing infection and severe illness

It also includes elements that are inherently much more uncertain such as:

- Effectiveness of interventions (masks, working from home, social distancing)
- Public behaviour over and above any public health measures (e.g. cancelling plans, reducing contacts)

Features of real life

Inherent randomness

Even if a model is perfectly structured and parameterised, the future is not determined.

For instance, a chance event might lead to a superspreading event or no onward infections. At a larger scale, unexpected events (e.g. weather disasters, political protests) might create conditions for a superspreading event accelerating spread or, conversely reduce transmission (e.g. a long period of good weather)

Teams normally deal with this uncertainty by running stochastic models thousands of times and reporting the central outcome and the range of possible outcomes seen in different realisations.

Context fundamentally changes

Slightly different to inherent randomness, is if the situation fundamentally changes over the timescale of prediction.

For instance, projections are run for 6 months with best current knowledge, but a new variant emerges and spreads, or new policy is brought in or measures are dropped. Any such even that fundamentally changes the context of the disease will render previous predictions invalid.

Modellers try to deal with this (and uncertainties within the model) by considering various scenarios (different policies, different variants, different behaviour), but reality usually does something different again.

Figure 1 - Sources of uncertainty that affect the accuracy of modelling scenarios. These need to be communicated – and more than once - to policymakers and the public.