NOTES AND INSIGHTS

Using system dynamics to support a functional exercise for pandemic preparedness and response

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Abstract

In pandemic preparedness and response, a Functional Exercise (FX) is used to simulate a situation as close to a real-life event as possible without the deployment of resources. Participants are drawn from public health emergency operations centres, and work through a scenario script to test possible responses to a novel pathogen outbreak. This paper summarises the role of system dynamics modelling in the design and implementation of a functional exercise, which involved the Dutch and German national public health institutes in March 2023. The findings confirm the value of the system dynamics method in integrating disease and hospital models, and also highlights how well the method aligns with modern software development processes. The paper concludes with a discussion of what worked well, and presents areas for future enhancements of management flight simulators to support functional exercises.

Keywords: functional exercise, pandemic preparedness, public health, resource planning, system dynamics

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Additional Supporting Information may be found online in the supporting information tab for this article.

Introduction

System dynamics (SD) modelling is well suited to address the dynamic complexity that characterises many public health issues (Homer & Hirsch, 2006) and has increasingly been used in the health-care domain over the last decades (Davahli et al., 2020). Despite this progress with SD modelling in health-care and health-care policy, even when new tools offer clear advantages, there are barriers to

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adoption (Minyard et al., 2018). To address potential obstacles, a participatory approach can help legitimise a new tool if a variety of end users are involved in its design and if the social and organisational context and typical workflows are considered (Liberati et al., 2017). Group model building (Richardson & Andersen, 1995; Vennix, 1999) and other forms of participatory model building (Brown et al., 2022; Stave, 2010) increase stakeholder contribution and engagement. Complementary methods such as Agile software development emphasise multiple stakeholder collaboration, can strengthen cooperation between health-care and software development professionals, and further improve the quality of software in health-care settings, and its use in health care is growing (Kokol, 2022).

In the context of public health, effective training platforms can greatly enhance emergency-preparedness exercises carried out by public health agencies and have assumed greater importance over the years (Gebbie et al., 2006). Modelling now plays a crucial role in enabling public health stakeholders to train personnel and formulate plans for different emergency contingencies (Araz, 2013). However, in the field of pandemic preparedness, most models have been primarily epidemiological, aimed at understanding the spread of the disease and the impacts of public health interventions on the dynamics of infection (Currie et al., 2020). Reviews of existing health-care resource models, their characteristics, and limitations identified a need to improve both the determination of likely resource deficits and the quality of resource-capacity-management decision-making (Currie et al., 2020; Lukács, 2022).

The EU funded PANDEM-2 project[i] aimed to address this gap and develop tools to support pandemic preparedness and response planning. Multifaceted and multidisciplinary, this project comprised: capture of heterogeneous pandemic data (surveillance), its integration, analysis and visualisation via a dashboard (data analytics), predictive tools for pandemic preparedness planning including expected infected and hospitalised cases and resource demand (system dynamics modelling), pandemic communications, training through simulation exercises, and ethical considerations such as data privacy and legal issues arising from pandemic management. The consortium members who informed model development included experts from public health agencies, hospital resource managers, senior clinicians and first responders in EU countries. This group of health experts were the main end users of the modelling tools and will be referred to in this article collectively as pandemic managers. The modelling work in the PANDEM-2 project built on AsiaFluCap (Krumkamp et al., 2011; Stein et al., 2012) and the PANDEM phase I project[ii] (grant agreement no 652868), specifically the PandemCap decision support tool (Yañez et al., 2017).

An important aim of the model-building process was to support the public health and emergency planning process, specifically a Functional Exercise (FX) which simulates a situation as close to a real-life event as possible without the deployment of resources. The FX provided an important opportunity to test the modelling tools with expert users and to obtain their feedback. The FX was

[i]PANDEM-2 project website. https://pandem-2.eu/ (Accessed 4 August 2023).
[ii]European Commission. *CORDIS EU research results*. https://cordis.europa.eu/project/id/652868/results (Accessed 4 August 2023).

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conducted at Public Health Emergency Operations Centres (PHEOC) of the Dutch and German national public health institutes in March 2023. The FX scenario script simulated the emergence of a novel avian influenza virus similar to the 1918 H1N1 strain with healthy young adults particularly vulnerable to severe illness and the lack of therapeutics and vaccines creating a health crisis. The FX included scenario planning tasks, which deployed the modelling tools developed during the project.

The aim of this article is to describe the role of system dynamics in the pandemic preparedness process and summarise the insights and value obtained from using system dynamics modelling to support the FX. The article also demonstrates the value of integrating model building with an iterative software development process in order to provide an interactive web-based simulator designed to enable end users to learn experientially about important concepts in pandemic preparedness, aligning it with prior system dynamics work on flight simulators (Sterman, 2014a; Sterman, 2014b). A full summary of the underlying model is provided in the online supporting information — Data S1 — including information on: (1) use cases prioritised by end users, (2) the model input parameter descriptions, (3) the dashboard screenshots, (4) the resource model structure, and (5) the modelling workshop survey and results.

System design

Model building process

The stages relevant to the FX are depicted in Figure 1 and reflect an iterative modelling and software design process which took place over a period of 2 years. Project partners at the National Institute for Public Health and the Environment (RIVM) conducted a systematic review and Delphi studies to identify essential pandemic resources to include in the model and to search for reported associated parameter values. Working with RIVM and the Radboud University Medical Centre, the modelling team of the University of Galway built the combined epidemiological and hospital-resources model, meeting regularly to demonstrate, test, and refine the model. The system dynamics modelling process provided the overall structure for model building (Sterman, 2000, p. 85). The resource modelling work fell primarily into the “pragmatic” school of thought within the system dynamics field (Clancy et al., 2023), in which the goal is to solve a problem in direct relationship with stakeholders to create management tools, and where quality is defined by stakeholder needs. The model was then integrated within the PANDEM-2 dashboard.

The dashboard was designed using the Scrum framework, an Agile software development process (Schwaber & Beedle, 2001) that emphasises collaborative development in rapid, incremental iterations, maximising the opportunity for feedback and improvement. For the modelling component, the modelling team interacted with a number of PANDEM-2 teams, including those responsible for user experience (UX), visual analytics (VA), server development, and pandemic managers.

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Model structure

The system dynamics model consists of three interconnecting modules, shown in Figure 2. The "epidemiological module" provides the flow of patients (hospitalisations) to the "hospital module," which models patient pathways and feeds information about current use of resources to the "hospital-resources module." The hospital-resources module provides availability of resources back to the hospital module, in order to constrain bed admissions. The epidemiological module also provides a disease-prevalence variable which drives infection in nurses (ICU and general ward) in the hospital-resources module. Further information on the resource-model input parameter descriptions can be found in the online supporting information (Section 2).

Three types of interventions which impact resource demand were requested: public health policies, in-hospital pharmaceutical interventions, and hospital-surge strategies. All aim to reduce cases, hospitalisations, morbidity, and/or mortality. Public health interventions can be applied early at the population level to reduce the number of new infections and at any point during the course of the pandemic. Once infection is widespread and patients are in hospitals,

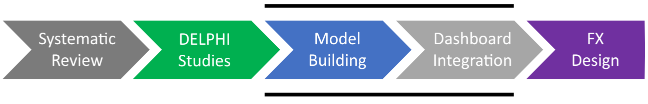

Fig. 1. Model, dashboard, and functional-exercise development process

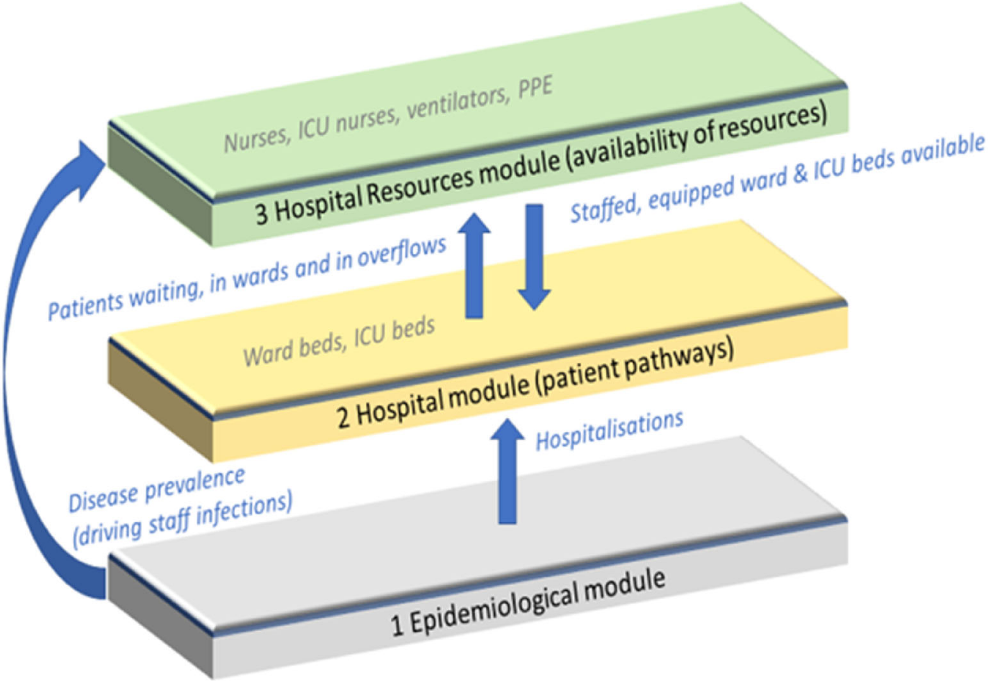

Fig. 2. The combined epi + resources model, consisting of three modules

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pharmaceuticals can be administered to reduce the severity of the illness. Hospital-surge strategies can be applied as a response if resources run low, to increase resource capacity, or to reduce resource usage. The interventions built into the model are listed in Table 1. The model is designed to support any combination of interventions. A further intervention is implicit in the model: preallocating a proportion of hospital resources for pandemic (as opposed to routine) use. This is done prior to the simulation run and defaults to 50%.

A high-level schema of the model within the dashboard is shown in Figure 3. Inputs include regional resource-capacity data and resource-usage rates. Disease severity inputs govern the flow of patients through the hospital and patient outcomes. Policy inputs specify which interventions have been chosen by the user. The system outputs follow end-user requirements captured in use-case format — see the online supporting information (Section 1). Descriptions of resource-related model input parameters are listed in the online supporting information (Section 4).

TABLE 1. Interventions built into the model, by type

Public health (EPI model)	Pharmaceuticals (hospital model)	Surge strategies (hospital model)
Vaccination	Antivirals	Reduce ICU nurse to patient ratio
Mobility restrictions	Previous strain vaccines	Reduce ward nurse to patient ratio
Testing and isolation		Reduce PPE per shift
Contact tracing		Increase physical ward bed capacity
Mask wearing		

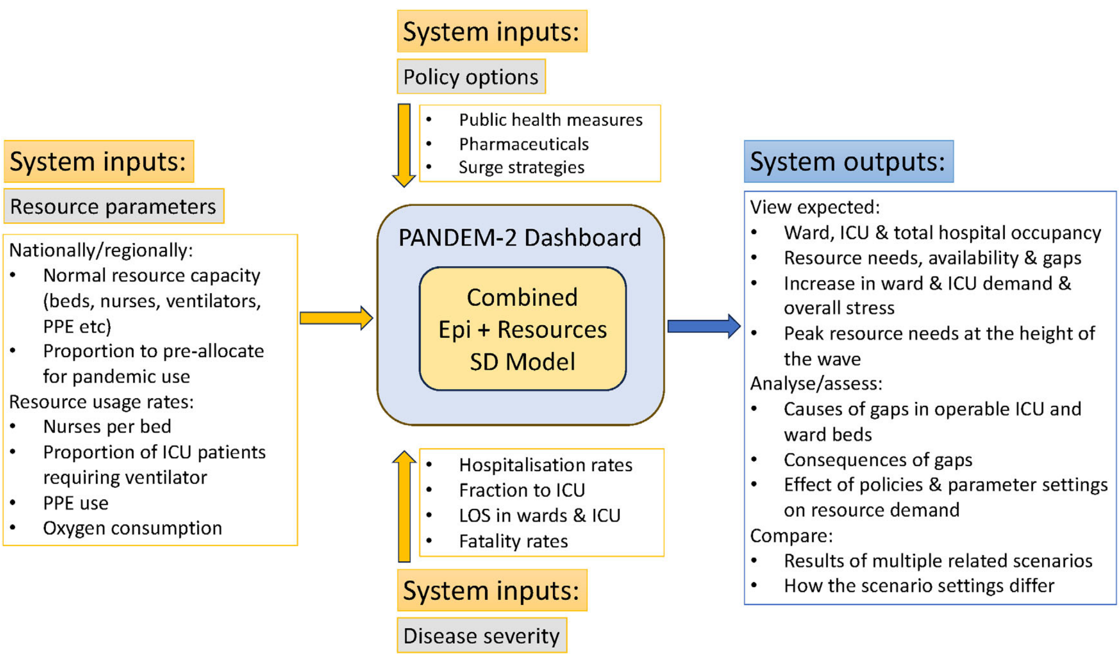

Fig. 3. The model within the dashboard, with overview of resource-related inputs and outputs

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Software architecture for model and dashboard integration

The software architecture is shown in Figure 4 and was designed to maximise flexibility for building a reusable model library. The combined epidemiological and resources model was established as a web service that runs Stella Simulator server. Application programming interfaces (APIs) were developed using the R Plumber library to support communication between the dashboard and the model. To allow for different models, the PANDEM-2 dashboard first makes an API call ("1a") to get details of the parameters required for a specific model, and these are returned with their default values ("1b"). The dashboard then collects necessary model input data ("2") from its own database, the default values provided ("1b"), and any adjustments made by the user before calling the main model simulation API ("3a"). This returns the simulated model output in JSON form ("3b"). The dashboard architecture is based on Angular, the open-source web-application framework, with data visualisations developed using Highcharts, the Javascript charting library. Charts are dynamically generated from data returned by the API calls ("4").

The functional exercise

Model and dashboard refinement

Once the dashboard modelling tools were in place, the modelling team worked to refine the model and dashboard in preparation for the functional exercise (FX), as shown in Figure 5. This involved defining a suitable set of realistic disease-severity parameters for the avian influenza disease at the centre of the exercise, and to define the modelling-related dashboard tasks. For the purposes of the FX,

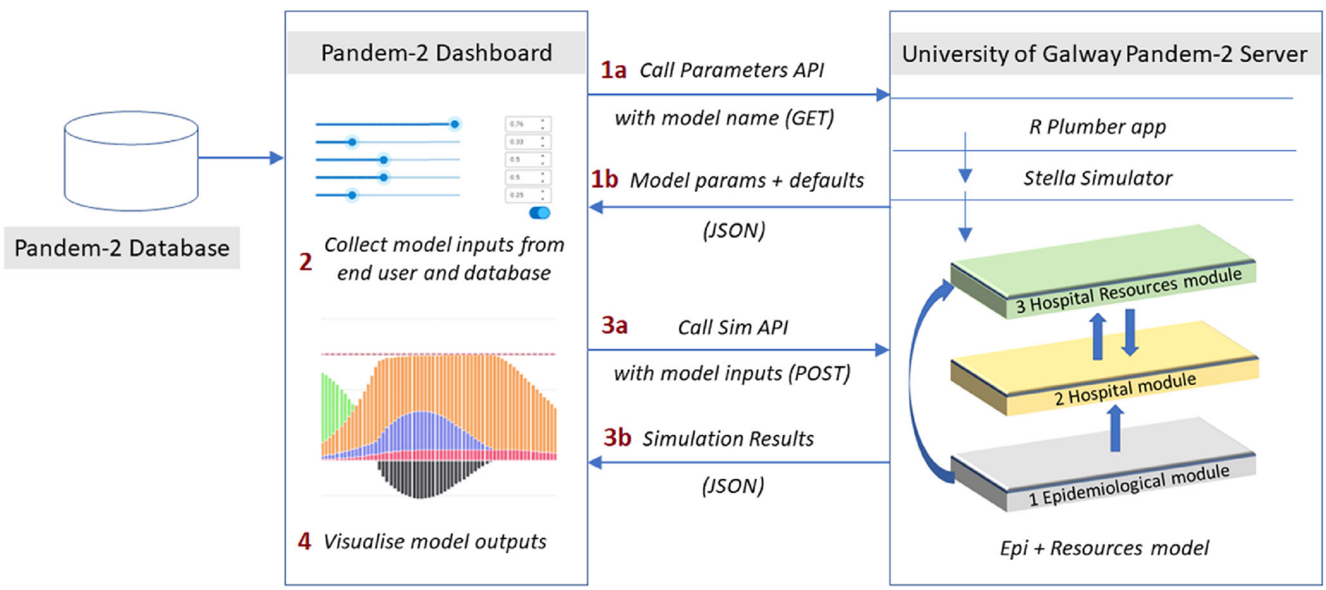

Fig. 4. Modelling tools software environment

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Fig. 5. Process of evaluation and model and dashboard refinement

the model was populated with synthetic data from Germany and the Netherlands, including population and contacts-pattern data, based on Dutch Official Statistics and contact estimates from POLYMOD (Mossong et al., 2008) within the socialmixr R package (Funk, 2024). Resource data was aggregated at the national level. The model is disaggregated by age, with four age cohorts: under 15, 15–24, 25–64, and 65+ years. These age groups are based on six age groups used by the ECDC when reporting COVID-19 cases,[iii] with the last two age groups combined.

Questions arising from the public health teams concerning repercussions of parameter and intervention options required demonstrations of the behaviour of the model. A Stella interface published online[iv] proved more suitable for these in-depth online cross-disciplinary discussions than the original Stella Architect model (.stmx). This interface was intended for internal project use and entirely separate from the PANDEM-2 dashboard. The two 20-minute modelling tasks chosen for the FX required users to find and compare the projected number of cases, hospital (ward and ICU) admissions, and bed demand and occupancy versus capacity, when different specific public health policies were active. The aim was to evaluate the risk of resource outage in the different scenarios.

Five weeks prior to the FX, participants attended a 2.5 h online dashboard modelling training workshop, which aimed to familiarise them with dashboard functionality so that they could carry out the FX modelling tasks. There were eight modelling tasks, three examining key epidemiological indicators under different scenarios (no intervention, vaccines, and mobility restrictions), and five examining the effects of various interventions (public health policies, use of pharmaceuticals, and hospital-surge strategies) on estimated resource demand and shortfalls. More information can be found in the online supporting information (Section 5). Eleven participants completed a postsurvey online within 3 days of attending.

The FX was then held online on 15–16 March 2023. Eleven public health experts from RIVM in the Netherlands and six from RKI in Germany participated. Nonparticipating observers from the project technical team noted how participants interacted with the software as they carried out the FX tasks, and an evaluation team collected written free-text feedback from participants during and after the exercise.

Model feedback and findings

The model demonstrated many expected behaviours. Public health interventions reduce hospitalisations, therapeutic interventions improve patient outcomes and

[iii]European Centre for Disease Prevention and Control. *Data on the 14-day age-specific notification rate of new COVID-19 cases*. https://www.ecdc.europa.eu/en/publications-data/covid-19-data-14-day-age-notification-rate-new-cases (Accessed 4 August 2023).
[iv]Published on the ISEE Exchange. https://exchange.iseesystems.com/public/caroline-green/explore-epi-plus-resources-pandemic-model/ (Accessed 4 August 2023).

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free up hospital resources, and surge strategies increase capacity but have negative side effects that can be explored. The model demonstrated that no single public health intervention can contain the spread of the pandemic, and so multiple policies must be deployed at the right time and with the right strength (Andrade et al., 2023). A lack of ICU increases reported deaths. A lack of component resources such as PPE, nurses, physical beds, or ventilators cascades to create a lack of operable beds.

Overall, feedback provided by workshop participants was very positive. Of the 11 postworkshop respondents, seven were public health experts, two were hospital managers, and two were first responders. Asked to rate, on a scale of 1–10, if they thought the tool would be useful for pandemic preparedness and response, they gave a median score of 9. Ten respondents thought the model was useful for supporting a pandemic-preparedness exercise. They found the tool well organised, clearly presented, and easy to learn (median scores 9 out of 10). All found the visualisation of multiple runs informative. Ten respondents found the resource indicators useful. Most found the patient pathways, surge strategies, and pharmaceutical interventions plausible and useful.

Qualitative feedback from participants was also insightful and included: the potential risks of oversimplification; conveying uncertainty or confidence limits; providing explicit definitions of terms such as “lockdown” and “stress code”; and requests for model transparency (structure and assumptions).

Discussion

Establishing trust in decision support tools under uncertainty is an important topic in modelling, simulation, and related fields (Begoli et al., 2019; Bhatt et al., 2021; Botz et al., 2022; Harper et al., 2022; Thompson et al., 2022). Adequate training, documentation, model transparency, and explicit guidance on reliability of results is needed for end users to be able to trust and know the limitations of such a tool. The system dynamics approach successfully supported the functional exercise and made a valuable contribution to advancement in tools for pandemic preparedness and response, being well received by experienced pandemic managers. We will now reflect on what worked well as part of this process and potential areas for future development.

What worked well

- An overall strength of the system dynamics method is that it facilitated interdisciplinary collaboration between modellers, public health and hospital professionals, and software development teams. Stock and flow diagrams, sector models, synthetic data generation, and the use of web-based implementations for highlighting structures and generating results were used throughout the project, and they proved to be valuable aspects of the project life cycle.
- The system dynamics modelling approach aligned well with the Agile software process, which was used to manage the life-cycle of the pandemic dashboard. Both methods supported an iterative approach to design and implementation, with frequent opportunities for feedback and improvements. The Agile method

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included a visual analytics design process that was used for visualising the model outputs and deciding on what performance indicators to prioritise. Example of the screenshots are shown in the online supporting information (Section 3).

- The design decision to separate out the simulation into a callable web service was advantageous for a number of reasons. First, it enabled model builders and developers to focus on the modelling as a "black box" with a clearly defined interface which accepted information (initial values for model stocks and parameter choices) and returned simulation data as results. Second, the decision to separate the simulation into a service meant that newer versions of the model can be implemented, without significant changes to the user interface.
- The use of the systematic review and follow-on Delphi study was a valuable input to the model-building process. The systematic review provided the means to identify key parameters and resources for pandemic planning and response, and the subsequent Delphi study facilitated a form of prioritisation process, where domain experts provided additional information on which resources should be part of the model. These included public health resources (e.g., vaccination capacity) and hospital resources (e.g., physical ICU beds, ICU nurses, and PPE).
- Deploying the underlying SEIR model to generate synthetic data based on disease parameters such as R_0 (where cases were generated via the Poisson and negative binomial distributions) was an advantage for the FX, as it allowed for realistic case data to be imported into the dashboard, and these were then used to explore a range of plausible disease trajectories.

Areas for future developments

- In a crisis, hospitals resources are rapidly "stretched" in a complex, responsive, and dynamic way (Adams, 2009). Further work is needed to incorporate common strategies such as increasing stockpiles of PPE and ventilators preemptively when a surge is predicted and stretching morgue capacity (e.g., by adding more shelving). This increases dynamic complexity, since nurses, already at risk of infection, also risk absence through burnout as a result of such surge strategies, and if overwork is prolonged, they are also more likely to leave the profession permanently (Poon et al., 2022; Rotenstein et al., 2023; Tabur et al., 2022). Building each surge strategy into the model involves not only defining parameters that change resource-usage rates but also parameters or structures that represent side effects or trade-offs (Oliva, 2001). The more surge strategies that are modelled, the more complex the model becomes, which may make it less useful as a learning tool (Ghaffarzadegan et al., 2011).
- A limitation of the model are that community care and home care are not included. These impact hospital resources because limited capacity in these facilities can hamper the "outflow" of hospital patients and "obstruct" the system. For example, discharge of patients with oxygen to their home (with home care) or a long-term care facility frees up hospital ward beds. The impact of pandemic demand on routine care is currently only conveyed using general indicators such as hospital stress. Projected effects would be improved by

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integrating pandemic and routine care. Resource sharing (Nijs et al., 2022) between regions and countries (starting with PPE and equipment or medicines) and patient transfer (burden sharing) would be useful additions to the model and would require disaggregation and resource data collection by region.
- In the closing months of the project during review discussions, and in the context of post-COVID-19 policy evaluations being held around the world, pandemic managers expressed an interest in incorporating consideration of longer-term negative health and social consequences of public health policies to help inform decision-making. Although these consequences are often multifaceted and hard to measure, modelling techniques such as using missed contacts (i.e., reductions in social interactions) as a proxy for societal burden have been used to try to model balancing the competing goals of reducing both cases and societal harm (Reymond et al., 2022).

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Berend Beishuizen is a researcher at the Centre for Infectious Disease Control at the Dutch National Institute for Public Health and the Environment. He is also a PhD candidate at the Department of Primary and Community Care of the Radboudumc in Nijmegen. His research areas include pandemic preparedness, antimicrobial resistance, and antibiotic stewardship.

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Claudia Houareau is a public health senior expert in infectious diseases and crisis management. She was part of the crisis management team at the National Public Health Institute of Germany, the Robert Koch Institute. She joined Capgemini Public Health in 2023 as a lead business analyst and is supporting the digital transformation of public health in Germany.

Knut Perseke is employed (since 2018) as a software developer and data scientist at the Robert Koch Institute. He is a member of the open data team and is responsible for publishing data sets for various communities, including data journalists and civic tech activists. His primary development focus lies in creating web-based dashboards for data analysis and exploration, specialising in data visualisation.

Clara Spieker joined the Robert Koch Institute in 2023, following the award of a Master of Public Health, which focused on Global Health. Clara works in the Unit for Crisis Management, initially as part of the EU Horizon project PANDEM-2, which involved planning and implementing a simulation exercise. She is now involved in other internal crisis management activities as well as the Unit for Gastrointestinal Infections, Zoonoses, and Tropical Infections.

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Ulrike Grote has worked at the Robert Koch Institute Berlin since 2016 — first in the Unit for Surveillance and currently in the Unit for Crisis Management. Her main focus is on the RKI internal crisis management as well as the design, implementation, and evaluation of simulation exercises. In addition, she is involved in various teaching activities in Germany and abroad.

Patrick Csornai is a software engineer from Romania. He graduated from the University of Oradea, where he studied Computer Sciences, and currently applies his expertise at Modus Create. Patrick is proficient in multiple programming languages and excels at developing dynamic web applications. In addition to his passion for technology, he has a keen interest in history.

Carlos Tighe is a Research Associate with the Applied Innovations team at the Insight SFI Research Centre for Data Analytics at the University of Galway. Initially a philosophy graduate, he transitioned to computer sciences in 2013 and has since applied his expertise to various industry-related research projects. He has worked in a variety of domains including mental health, pandemics, energy management, and more recently marine spatial planning.

Conor Hayes is a Senior Lecturer in the School of Computer Science at the University of Galway. His research interests are in the fields of Data Visualisation, Human Computer Interaction, and Graph and Network Analytics. He has carried out research at the Bruno Kessler Institute in Trento, Italy and as a Principal Investigator at the Insight Centre for Data Analytics, Ireland.

Jair Andrade is a research associate at the University of Cambridge. Previously, he held a postdoctoral position at the University of Galway. His work combines statistical inference and model simulation to investigate infectious disease dynamics.

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Supporting information

Additional supporting information may be found in the online version of this article at the publisher's website.

Data S1. Supporting information.

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