Grand Challenges in Healthcare Simulation

Laura M. Boyle, Christine S.M. Currie, Thomas Monks, Lucy E. Morgan, Alexander R. Rutherford

February 13, 2026

Word count: 10018

Abstract

The paper describes grand challenges in healthcare simulation for the next ten years. We consider challenges within seven themes that are likely to have the greatest impact on healthcare simulation during the next decade: digital twins and real time simulation, open science for simulation, validation, improving the integration of the health system, decision support, including human behaviour, equity and health inequality. Drawing on previous work in the area, we suggest directions that healthcare simulation research may follow and the associated challenges. Our aim is to help shape the research agenda in this important area.

Keywords: Simulation, healthcare, grand challenges, discrete event simulation, agent based modelling, system dynamics

1 Introduction

President Barack Obama introduced a series of grand challenges during his time in office, describing them as "ambitious but achievable goals that harness science, technology, and innovation to solve important national or global problems and that have the potential to capture the public's imagination," *21st Century Grand Challenges* (n.d.). Although capturing the public's imagination is less relevant in our case than it would be for a political party or a government, it is important that we solve problems that are relevant outside the academic bubble. The challenges we describe below are a mixture, with some designed to address topical problems in healthcare and others that aim to take advantage of new advances in modelling and simulation and apply these to healthcare problems. The challenges should be achievable within a decade as looking further ahead is dangerous in a fast-moving research area.

As a simulation community, we have developed grand challenges in simulation around once per decade with the original Workshop on Grand Challenges for Modelling and Simulation (M&S), held at Dagstuhl in Germany in 2002, organized by Richard Fujimoto, W. H. Lunceford, Jr., Ernest H. Page and Adelinde M. Uhrmacher (Dagstuhl 2002). A subsequent panel session was run at the Winter Simulation Conference (Taylor et al. 2012), with similar panels at SpringSim and the first SIGSIM-PADS conference, both in 2013. The results of these panel discussions are summarised in Taylor et al. (2013) in which Sally Brailsford stated the main challenge for healthcare M&S was around implementation, citing generic or generalisable models as a possible way of both ensuring widespread application of simulation models and avoiding reinventing the wheel. Simulation reuse is picked out again in what follows as an area where advances could be very beneficial to healthcare simulation.

It is interesting to look back on the grand challenges set out for simulation methodology and think how these impact on the grand challenges for healthcare simulation. In 2016, Barry Nelson suggested that the new challenges in *analysis methodology*, the research area related to statistical challenges of simulation modelling, were a result of three key developments (Nelson 2016). First, cheap and effective data storage; second the ease of carrying out parallel simulations; and third the growing interest in risk analysis, prediction and control rather than system design. He went on to describe the then nascent field of simulation analytics. This was picked up later that year by Charles Macal (Macal 2016), who gave an overview of agent-based simulation (ABS) and described current challenges. Among these, increasing credibility and transparency in ABS is particularly relevant in healthcare and is touched on below, but also a need for increased use of hybrid models and the development of large-scale simulations. The challenge and opportunity of Industry 4.0 for simulation is described in Xu et al. (2016), who describe how simulation optimisation can be used to support operational decisions, drawing on real-time data from the system. These ideas feature in the topic areas we describe below: improved ABS that incorporate more data on individuals; education and open science to improve the transparency of modelling; and the use of digital twins to support real-time decisions.

The aim of this paper is to draw on expertise and experience to determine the grand challenges in healthcare M&S in order to set the research agenda for the healthcare simulation community. The suggestions included below draw on a panel session at the Winter Simulation Conference in 2022, discussions at ORAHS 2024 and subsequent discussions between the authors. While the fundamentals of healthcare are the same across the world, the practice and, in particular the funding of healthcare, varies between different countries. We are aware that we represent only a small number of countries and there may be challenges for simulation within other healthcare systems that we have not identified in this work.

The paper is split into seven themes, chosen to represent the broad areas that we believe will be most important to the future direction of healthcare M&S. These areas have been chosen as a result of their importance to global health and the possibility of methodological insights. Many of the key ideas we discuss match the ideas for future directions of research in Operational Research (OR) in healthcare described recently by Beliën et al. (2025), but our categorisation is different as we organise by methodology rather than application area and focus on topics most relevant for simulation research. The areas are as follows: digital twins and real time simulation; open science for simulation; validation; improving the integration of the health system; decision support; including human behaviour; equity and health inequality. Within each area we provide a description of its scope, an overview of recent literature and a discussion of the important future directions. Most importantly, each section concludes with a list of challenges. At the end of the paper we draw some general conclusions and combine the challenges together into five grand challenges, which synthesize these more detailed challenges around some common themes.

2 Digital Twins and Real Time Simulation

The increase in the amount of real-time data that systems produce has led to opportunities for developing methods that utilise these data to feed simulation models that can forecast the near future (e.g. Hoot et al. (2008)) and support operational decisions. Understanding the potential impact of digital twins on healthcare and how the M&S community can learn from their application in other areas to make them work in healthcare is an important topic. Below we define digital twins and then go onto discuss potential application areas and obstacles to their implementation before describing this theme's challenges.

2.1 Introduction to Digital Twins

A digital twin is a virtual or digital counterpart of a real system that should reproduce its important features, allowing the digital twin to be used for forecasting and decision-making. Biller et al. (2022) includes a set of required characteristics for a digital twin developed by the Digital Twin Consortium: a physical representation; a virtual representation; synchronisation between physical and digital representations at a pre-specified frequency and fidelity; an ability to learn and adapt that leads to improved virtual models and enhancements in physical representations.

Key to digital twin technology is that there is a two-way flow of information, allowing updates of the system state to be transmitted to the digital twin and recommendations and/or forecasts to be transmitted to the real system. A digital twin need not be a simulation model but could be a machine learning (ML) or statistical model. Within engineering, the digital twin may be used to describe a physical object or process and the most common use of digital twins in healthcare is in personalised medicine, where the digital twin describes the patient's health state. We focus instead on cases where the digital twin describes a health system. There is still some ambiguity in the terminology and authors have used the term *symbiotic simulation* (Onggo et al. 2020) or *real-time simulation* (Harper, Mustafee & Pitt 2023) to describe modelling paradigms that are very similar to digital twins.

Two ways in which digital twins have been used for process modelling are as follows.

- *System monitoring.* A model is constantly running in the background being fed by real-time data and will issue an alert when there is a problem, perhaps also returning a potential solution.
- *System analysis.* The digital twin is used to run a query using the current state of the system as an input. Typically it would output the best policy to follow but it could just be used for forecasting.

Within healthcare, system monitoring can be useful for providing early warning of problems within a hospital. For example, Hoot et al. (2008) forecasts crowding in emergency departments (EDs) and Oakley et al. (2020) design a whole hospital model that assesses the likelihood of demand exceeding supply. Their work continues into system analysis as they also evaluate revisions to the elective admissions schedule based on up-to-date data on the state of the hospital.

2.2 Applications of Digital Twins in Healthcare

Digital twins and real-time simulation are particularly useful for short-term, operational decision-making. Due to the need to account for patient care, we anticipate the majority of digital twin systems having a human in the loop rather than implementing automated decisions.

We are aware of more work modelling EDs than other areas, perhaps due to the focus on short-term decision-making. Heib et al. (2023) develop a digital twin discrete event simulation (DES) model that aims to optimise real-time allocation of staff to account for surges in demand. Forecasting future usage levels in the department based on the current situation is covered in Hoot et al. (2008), and these ideas are extended in Harper & Mustafee (2019*a*), which describes a hybrid simulation model that uses forecasting to trigger simulation experiments. One of the key advantages of using a digital twin in these cases is being able to simulate future trajectories from the current system state, which Hoot et al. (2008) shows produces more accurate forecasts of usage.

Other areas with the potential to benefit from digital twin simulation methods include ambulance dispatch; intensive care modelling; and bed planning. As we discuss in the next section, there are challenges to implementing digital twins that may have made them slower to in healthcare settings than in other applications such as manufacturing.

2.3 Obstacles to the Development of Digital Twins in Healthcare

A lack of availability of high-quality real-time data is the biggest obstacle to the use of data-driven simulation methods. While many hospitals are moving to digital recording of activities, there are many examples of either paper records or delays in data becoming available and accessible on hospital systems. The time stamp data that are typically collected may also not be ideal model inputs. For example, transaction data may record the start time of each activity but not the finish time, making it difficult to estimate distributions for activity durations.

As with all simulation modelling, poor training data can result in bias in the output results. This has the potential to be exacerbated where models are being parameterised automatically, without sufficient oversight. Understanding how the inability to obtain high quality, detailed, real-time data impacts on the accuracy of the recommendations is important. This may also help to reduce the amount of information that is transferred, improving the speed of the computation without reducing the quality of the solution.

Run speeds of simulation models can also be prohibitive. Real-time decision-making requires results to be returned quickly and when the model is being designed for decision support, fast simulation optimisation methods should be considered, as discussed in Xu et al. (2016).

Security concerns are a major obstacle to the development of digital twins in healthcare as cyber attacks can have many implications. The connection between digital model and physical system is a point of risk that could be exploited to gain access to data and information on the operation of the physical twin. At the extreme, with a closed-loop model, this could also provide opportunities to corrupt data or cause undesired effects in the real-world system. Any future healthcare digital twin will need to be designed securely. We do not include this as a challenge for simulation researchers as it lies within the field of cyber-security but raise it as a potential obstacle to implementing digital twins in health systems.

2.4 Integration with Agentic Artificial Intelligence (AI)

An area of opportunity for Digital Twins in healthcare is integration of AI methods and in particular AI Agents and multi-agent systems. An agent can be thought of as autonomous software that perceives its environment, makes decisions, and takes actions to achieve specific goals, often learning and adapting over time. Unlike traditional AI models, agents can operate independently, plan, and execute multi-step tasks without continuous human input (Sapkota et al. 2026). Contemporary agent methods employ Large Language Models (Brown et al. 2020), such as Anthropic's Claude or Meta's Llama for planning and reasoning about tasks as well as a range of other tools available within its environment.

In an agent paradigm, a Digital Twin becomes one of several tools available to the agent; for example, a human surgery planner might prompt an agent to help them optimise a draft schedule over a seven day planning period. An agent coordinating this task may orchestrate multiple specialised agents: simulation agents that operate the Digital Twin, optimisation agents that refine schedules, and communication agents that interface with hospital booking systems and patient contact systems.

An agent may decide to perform additional tasks before or after the Digital Twin is run. For example, based on the predictions of the Digital Twin, the agent may set up and run a specialised simulation-optimisation procedure, summarise and report findings and alternative schedules to the human user, or in cases where waiting lists permit, provisionally book patients for surgery and contact them with updated scheduling information. Agents might also periodically monitor real-world conditions and re-run the Digital Twin to provide dynamic adjustments to schedules as the state of the hospital begins to deviate from the simulation. Given the critical nature of healthcare decisions, these agent systems would maintain human oversight at key decision points; for instance, requiring surgeon approval before scheduling modifications that affect patient care pathways or resource allocation. Such implementations would rely on the systems being user-friendly and easy to use.

2.5 Challenges for Digital Twins and Real Time Simulation in Healthcare

Challenge DT.1 Generate a set of success stories of how digital twin simulations are used in all aspects of real healthcare systems. It is important that these examples are reproducible to allow sharing of best practice and enable a better practical understanding of how data-driven simulation can be useful.
Challenge DT.2 Create reparameterisation and hot-start methods that are robust to the data not being available or being of a low quality. These should include ways of reducing bias in the outputs due to inaccurate, out-of-date or unbalanced data. This is particularly important in cases where we are using patient characteristics to guide the model recommendations.
Challenge DT.3 Develop methods for quantifying how much state information is needed in order to make a good decision. The state information we refer to here is the data on the current status of the system that is passed to the simulation model before requesting decision support.
Challenge DT.4 Determine best practice for human-in-the-loop decision-making via real-time or digital twin simulations. This will include work on best practice for the presentation of results and is important for encouraging the use of digital twins, particularly where complex simulation optimisation methods are used. The aim should be that decision-makers have an accurate picture of the confidence they can place in the results.

3 Open Science for Simulation

Open Science aims to make research processes and outputs widely accessible, promoting transparency, credibility, and reuse of computational artefacts (Pouwels et al. 2022, Munafò et al. 2017). In simulation, this represents a shift from publishing only journal articles to sharing research artefacts throughout the study lifecycle: conceptual models, computer code, data preprocessing scripts, and peer reviews. In Open Science terminology these are referred to as research *artefacts*. Computer models can be permanently archived online with licenses that enable reuse and proper attribution. When implemented using Free and Open Source Software (FOSS) (Dagkakis & Heavey 2016) and web technologies (Wojciechowski et al. 2015, Monks & Harper 2023*b*, Smith & Schneider 2020), models become more accessible to diverse users. One such example is the New Hospital Programme (NHP) Demand model by The Strategy Unit (Strategy Unit 2026), which aims to provide a nationally consistent, transparent model to guide and inform hospital and community healthcare planning by forecasting future demand for inpatient healthcare as well as scaling potential opportunities for the left shift from secondary care to neighbourhood health. The model code is fully open sourced and fully documented and is being used in Trusts across the nation.

Open Science encompasses several dimensions including Open Data, Open Materials, Open Methodology, Open Access, and Preregistration of protocols (Haim et al. 2023), as well as Open Infrastructure and Open Policy (Taylor et al. 2017). Research studies may only be partially open across these categories; for example, publishing electronic health records is often legally complex, but researchers can publish metadata documenting extraction criteria or synthetic data (Gomes et al. 2022) to enable verification and reuse.

3.1 Open Science initiatives in simulation

3.1.1 Reporting Guidelines

Open methodology, particularly meticulously documented simulation models and studies, can be supported by existing simulation reporting guidelines. These guidelines take various forms: from general guidance to worked examples to structured checklists. The latter is more popular in health research, with many guidelines published on the Enhancing the QUAlity and Transparency Of health Research (EQUATOR) network[1].

Key simulation reporting guidelines include: the 'ODD' (Overview, Design concepts, and Details) protocol for ABS (Grimm et al. 2020, 2010, 2006); the Strengthening the Reporting of Empirical Simulation Studies (STRESS) checklists for DES, ABS and system dynamics (SD) (Monks et al. 2019); ISPOR-SDM general principles (Eddy et al. 2012); minimum and preferred reporting checklists for SD models (Rahmandad & Sterman 2012); and a generic checklist for DES in Health Economic Evaluation (Zhang et al. 2020).

These guidelines differ in their support for Open Materials and Open Data. ISPOR-SDM encourages non-confidential model sharing to enhance transparency but does not mandate it. Zhang et al. (Zhang et al. 2020) focus solely on logic and validation without prompting for material availability. STRESS similarly includes prompts rather than requirements for making materials and parameters available, including how models can be accessed. In contrast, the preferred requirements of Rahmandad & Sterman (2012) ask users to publish source code. Both STRESS and the preferred SD reporting requirements require detailed software environment and hardware specifications.

3.1.2 Initiatives to Test the Reproducibility of Simulation Results

The Association of Computing Machinery (ACM) defined reproducibility as the ability of different researchers to recreate the results of a simulation study using the same research artefacts as the original researchers. Research can be verified as reproducible privately without model code being published openly; e.g. within an academic institution or as part of a closed peer review process. It is therefore useful to distinguish between reproducible research and *open reproducible* research.

The ACM Replicating Computational Results (RCR) [2] and the Journal of Simulation's Model Reproducibility Initiative (JOS-MRI) [3] offer optional peer review of computational artefacts. Referees provide an open report on the method and review outcomes, awarding badges such as 'artefacts available' or 'results replicated'. Both initiatives validate 'results reproduced' (using the original artefacts), while ACM also offers a badge for 'results replicated' (using independently coded artefacts).

These initiatives are currently limited to specific simulation journals. Healthcare simulation authors publish in diverse journals outside of this portfolio that lack reproducibility review infrastructure. Thre are also some challenges for the initiatives: reviews require substantial reviewer time, and may be infeasible where hardware or software is complex, proprietary, or computationally demanding. However, hardware limitations are relatively rare in healthcare simulation, where standard packages like Arena and Simul8 dominate for low-to-medium complexity models (Monks & Harper 2023*a*), though reviewers still require proprietary software access.

[1] `https://www.equator-network.org`
[2] `https://www.acm.org/publications/policies/artifact-review-and-badging-current`
[3] `https://www.theorsociety.com/ORS/ORS/Publications/JOS-MRI.aspx`

3.1.3 Free and Open Source Software and Supporting Infrastructure

Recent initiatives to support Open Materials in computer simulation in health have begun to leverage FOSS and its related online infrastructure and tools. In FOSS, *Free* stands for *Freedom* and not cost to a user and this is operationalised by *open licensing* that grants rights (freedoms) and terms for others to reuse, redistribute the original, adapt, and publish derivative software and code. These are often referred to as the four essential freedoms of FOSS[4]. There are many licenses available that grant the freedoms while removing author liabilities for reuse, protecting patents, controlling future licensing, and making it a legal requirement to credit the original authors. We refer readers elsewhere for more details (Taylor et al. 2017, Monks et al. 2024, Janssen et al. 2020). When a license is not included, software and code is not FOSS. Authors retain exclusive copyright and legally others do not even have the essential freedom to run the software. A simulation author must explicitly grant others the four freedoms to reuse their computer model.

FOSS simulation projects that support Open Materials include developing novel modern simulation packages such as *ciw* (Palmer et al. 2019, Palmer & Tian 2023), tutorials in R and Python for creating and deploying runnable versions of models on the web (Monks & Harper 2023*b*, Smith & Schneider 2020), and methods for automating packaging and deployment of models (Smith et al. 2023, Harper, Monks & Manzi 2023). To complement these FOSS studies, open infrastructure has also been introduced to enable long term archival of open models, and facilitate discovery. Relevant model archives include the Peer Models Network (Harvard et al. 2022), and the The Network for Computational Modelling in the Social and Ecological Sciences (CoMSES Net; Janssen et al. (2008)). These are dedicated model archive sites and in the case of CoMSES Net support model citation via a Digital Object Identifier. Other more general archival tools exist that offer similar benefits such as Zenodo[5] or academic institutional archives.

3.2 How Open is the Healthcare Computer Simulation Literature?

A systematic scoping review of 564 DES studies in healthcare from 2018 to 2022 provides a limited view of the field's openness (Monks & Harper 2023*a*). Of these, only 47 (8.3%) cited a published computer model, and just 29 were open models utilising FOSS. In total, 72 studies that used FOSS simulation tools did not share their code. Best practices were rarely followed with less than half of the published models including an open license, failing to grant essential reuse freedoms, and only seven were permanently archived and citable. This puts the majority of published models at risk of being lost to the community. While 72 (12.8%) of the studies mentioned using a reporting guideline, the review did not assess the quality of the documentation. The healthcare DES literature appears less open than ABS models. A 2018 review of 7,500 articles found that 18% of ABS models were available (Janssen et al. 2020).

Even when models are shared, there is no guarantee that the results are simple to reproduce. An empirical assessment of eight openly shared healthcare DES models found that reproducing results required up to 28 hours of troubleshooting per model, with only half being fully reproducible (Heather et al. 2025). The primary barriers were the absence of open licenses, discrepancies between reported and coded parameters, and missing code to generate outputs and figures. The study concluded that the authors could address these issues with relatively little effort by including an open license and sharing all materials used to produce the article.

[4]`https://www.gnu.org/philosophy/free-sw.html`
[5]https://zenodo.org/

3.3 Barriers to Open Science

In health, medicine, and biology, a number of surveys have been completed to understand attitudes and barriers to Open Science practice (Pouwels et al. 2022, den Eynden et al. 2016, Samota & Davey 2021, Hrynaszkiewicz et al. 2021). A general finding is there is perceived benefit from Open Science. For example, a survey in health economic evaluation (Pouwels et al. 2022) found that the researchers believed that open source models increase transparency (92%), efficiency (76%), reuse (86%), and credibility (75%). Although Open Science is viewed positively, overall uptake of open practices in research remains low due to a number of perceived and practical barriers.

3.3.1 Barrier 1: Open Science Knowledge

In general, a substantial barrier to Open Science is a lack of relevant education and training. Early to mid career researchers (ECRs) have been shown to be more willing to engage with Open Science and good research practice (Hrynaszkiewicz et al. 2021), but also report that they do not have the required knowledge or are not fully supported in the the uptake and implementation of Open Science (Zečević et al. 2021, Gomes et al. 2022). One explanation for ECRs not publishing code is insecurity and lack of confidence in the standard of code they have produced (Gomes et al. 2022, den Eynden et al. 2016, Hrynaszkiewicz et al. 2021). In the UK, the Wellcome Trust (den Eynden et al. 2016) has called for the need for increased training in research to support code development standards, documentation practices, and licensing.

3.3.2 Barrier 2: The Work Associated with Open Science

Adopting an Open Science approach to research involves modified or new research workflows, and potentially additional work to undertake within a simulation study. The time commitments required to share models are frequently reported to be a disincentive for researchers (den Eynden et al. 2016, Hrynaszkiewicz et al. 2021, Gomes et al. 2022, Nature Biotechnology 2019). This work can include annotating and quality control of code, data, software dependency management, containerisation, and documentation. To mitigate time requirements, it is recommended that Open Science workflows to spread the effort required over time are designed into studies from the beginning (Allen & Mehler 2019). In the context of healthcare simulation, Monks & Harper (2023*a*) found that researchers using Github tended to have only a small number of commits; this could be as low as 1 included at the end of project to commit the final model.

3.3.3 Barrier 3: Concerns about Open Materials

Pouwels et al. (2022) surveyed the Professional Society for Health Economics and Outcomes Research (ISPOR) and identified concerns about inappropriate reuse of computer models by third parties (misuse), including unregulated model modification. A limitation of the survey is that it does not consider knowledge of open licensing options, which can, for example, permit reuse, limit commercial use, require attribution, or require all derivative work to also be released under the same license terms. The survey also did not explore attitudes towards potential misuse following recreation of well-documented models from journal articles.

A secondary concern is *scooping*, where materials are used by others to conduct analyses the original authors had planned but not yet completed, potentially harming academic careers. However, others argue that scooping risk is overstated and that Open Science benefits should be weighed alongside concerns (Gomes et al. 2022). For example, Open Materials and Open Data improve early career researchers' citations, collaborations, and funding opportunities (McKiernan et al. 2016).

3.3.4 Barrier 4: Methods for Simulation using FOSS

Although simulation is a mature discipline, relatively little research has been conducted into novel methods to enable reuse of computer models developed using FOSS. Barriers include installation of models, accessibility (ease of use) of FOSS models versus models developed in commercial software, and the availability of packages supporting hybrid simulation.

In healthcare, it may be both researchers and health services that wish to reuse and adapt computer models. Both categories of user may be blocked from reusing a FOSS model due to complex installation requirements and software dependencies. Remote hosting of models with browser based interfaces has been proposed as a potential solution (Smith & Schneider 2020, Monks & Harper 2023*b*), but these solutions do not help health services that have sensitive data/parameters that cannot be uploaded to a remote service (Smith et al. 2022).

The use of hybrid simulation, combining DES, SD, and ABS, is on the rise in healthcare (Kar et al. 2022). These models are typically implemented in AnyLogic. In the FOSS ecosystem, *Ciw* provides a demonstrable method to hybridise DES and SD models in FOSS (Palmer & Tian 2023), while the Business Prototyping Toolkit *bptk-py* allows for hybrid SD and ABS models (Schroeck 2020). However, the lack of a unified FOSS framework covering all three methods substantially limits the use of FOSS for hybrid simulation. Researchers making use of Anylogic can openly publish models, but others must then purchase an appropriate license in order to reuse or adapt models for research or application in a health service.

The most popular FOSS for DES in health are written in Python or R (Monks & Harper 2023*a*). Models are typically code based with limited options for animation (*salabim* being an exception; (van der Ham 2018)), and no user interfaces for model building and experimentation. In comparison to commercial simulation software, this can pose an accessibility (ease of use and high learning curve) barrier for new users. There is limited literature proposing methods to increase accessibility of FOSS models (Monks & Harper 2023*b*, Smith & Schneider 2020, Wojciechowski et al. 2015). In many cases this barrier may force users to abandon FOSS tools and a full Open Science approach in favour of commercial simulation tools.

While simulation's value in healthcare is clear, model reuse remains limited. Most healthcare simulation studies do not openly share computer models or adhere to Open Science best practice. An overarching grand challenge for Open Science in computer simulation is to increase the quality and volume of Open Data, Methods, and Materials to enable model reuse in research and health services.

3.4 Challenges for Open Science in Healthcare Simulation

Challenge OS.1 Create a comprehensive body of training materials to support open science workflows for computer simulation. This should cover simulation development using FOSS, open licensing and intellectual property, documentation and archival best practices, and deployment and maintenance of models. Training materials should be open, modifiable, and easily discoverable.

Challenge OS.2 Develop methods and tools to reduce the time and effort barrier associated with open science practices. This includes streamlined approaches to documentation and deployment; solutions to the installation problem for models with both public and private data; improved discoverability through standardised metadata.

Challenge OS.3 Enable and simplify hybrid simulation methodologies in FOSS environments. Currently, hybrid simulation combining DES, SD, and ABS is predominantly implemented in commercial software like AnyLogic. While FOSS options exist for specific pairings, the fragmentation of these methods limits accessibility and model reuse in healthcare. The challenge is to support all three methods within a simple unified FOSS framework.

4 Validation

Validation is the process of determining whether a simulation model accurately and credibly represents the real-world system it is intended to simulate. Without a validation procedure we cannot be sure the simulation outputs are sufficiently accurate, or that system behaviour has been captured well.

In simulation in general there are two strands to validation that when combined, provide the evidence to defend model predictions. The first of these involves examining the internal components of a model, including logic and input distributions, to ensure that individual elements accurately reflect the real-world system being modelled. Due to the complexity of healthcare systems, this step is essential in healthcare simulation to ensure the modeller (often not a clinical expert) has captured key behaviours correctly. Involving model stakeholders in this process can be a key to building model trust; see Tako & Kotiadis (2015), who outline a process for facilitated modelling. Within this process a modeller will consider the balance of complexity vs. accuracy within the model. Robinson (2023) includes a discussion on the benefits of simple models.

The second strand of validation involves comparing the model output to observations from the system of interest within a period where the system has been observed. For traditional simulation studies, i.e., where a model is used offline, parameterised with historical data, and is used to make one-off policy or operational decisions this procedure is carried out once to check for alignment between the model outputs within a historic period. Whereas for digital twins and sustainable/reusable models this procedure needs to be repeated, possibly many times. This is where many of the grand challenges for validation lie in healthcare simulation due to barriers on data access. However there is also an argument that as a scientific/simulation community we should be advocating for better data collection that would improve the process of model validation for digital twins and beyond. For an in-depth look at building and validating simulation models see Law (2022).

Within the NHS there has been a shift to using TREs (trusted research environments). A TRE is defined within the Goldacre review, (Goldacre & Morley 2022), as a secure analytics platform designed to facilitate access to NHS patient records data for research and analysis while minimizing privacy risks and maximizing public trust. The goal is to be secure, transparent and robust, and avoid the need for data dissemination to countless individual sites. Whilst important for protecting patient information, such environments can block the establishment of automated links between data and a model and thus the construction and validation of digital twins. The additional knock on effect of this is that making decisions in real-time (simulation for operational decision-making) becomes infeasible. One output the Goldacre review (Goldacre & Morley 2022) is the recognition that continuing with current practices risks missed opportunities, data access monopolies, outdated working methodologies and unnecessary duplication all of which come at high cost. In the United States (US) work is progressing towards a centralised country-wide TRE with the claim that this will enable a unified approach to health data exchange for, amongst other benefits, quality improvement and scientific research, see (Abbasi et al. 2025). Section 2 includes more detail on challenges specific to digital twins. The validation challenge therefore concerns how we validate real-time behaviour of adaptive simulation models in a tightening regulatory environment.

This challenge is remedied to some extent by the release of public datasets. In recent years the amount of publicly available healthcare data released directly by the NHS, the Office for National Statistics (ONS), registries or healthcare studies has been increasing. However, the lag between data collection and data release, often due to internal validation checks, can be lengthy, meaning the validation periodicity can be long. This goes against the real-time nature of digital twin models and could lead to a drop in model performance between validation exercises. There are also always questions around the data quality of these releases, and the lack of granularity of the data can limit the ways in which it can be used.

There has been interest in producing synthetic datasets for use in health research that in some cases are applicable to validation. Synthetic datasets share the same data structure and some or all of the statistical properties of the original data; for example, variable names, data types, univariate distributions or correlation across variables, but do not contain specific data relating to any real individual. In effect, they are a data set of simulated individuals. At the time of writing, in the UK examples include the NHS's Artificial Data Pilot[6] and Clinical Practice Research Datalink (CPRD) synthetic datasets[7]. Synthetic datasets are modelled directly on the raw data. Methods to generate the datasets can be as simple as univariate sampling, but some attempt to preserve relationships in the original data using Bayesian Networks and also ensure that original patients cannot be re-identified using differential privacy (Tucker et al. 2020). In England, researchers can also apply for access to GP records via Open Safely[8] a secure, transparent, open-source software platform for analysis of electronic health records data. Researchers build queries and analyses on synthetic data sets before sending off their code to be run on the real data. In this way patient data is never moved outside its secure environment.

For simulation in general, the rise of interest in digital twin models has driven the need for new methodology enabling continual validation. Questions exist around the optimal periodicity of validation and the optimal inclusion of input data. Bitencourt et al. (2025) provide a literature review of validation for digital twins and conclude that there is a lack of a standard methodology for the validation and verification of digital twins. Recent methods include the work of Rhodes-Leader & Nelson (2023) for identifying misalignment between twins in the presence of stochastic noise, Laidler et al. (2025) who provide a means for dynamic model validation using shapelets and Morgan & Barton (2025) where statistical process control methods are performed on a Fourier transformed queue-length simulation trajectory which can be used to identify divergence between the real-world and twin.

4.1 Challenges for Validation in Healthcare Simulation

Challenge V.1 Determine how we can validate real-time behaviour of adaptive simulation models in a tightening regulatory environment.
Challenge V.2 Support the creation of high fidelity synthetic data sets and use these to validate simulation models.
Challenge V.3 Advocate for better data collection aligned with modelling needs.

5 Improving the Integration of the Health System

Healthcare systems are highly complex and composed of numerous interconnected components. This makes it extremely difficult to predict their overall behaviour by simply considering each individual component (World Health Organization 2012). This section discusses the extent to which simulation has been used to model integrated healthcare systems. We then discuss the importance of, opportunities for, and obstacles to developing integrated healthcare simulations, and present the grand challenges in this area.

[6]https://digital.nhs.uk/services/artificial-data
[7]https://www.cprd.com/data/synthetic-data
[8]https://www.opensafely.org/

5.1 Integrated Healthcare Simulation Modelling

The majority of healthcare simulation studies tend to focus on individual units such as EDs or surgical suites, with comparatively fewer studies attempting to model multiple healthcare units or systems (Brailsford et al. 2019). Five different forms of integrated models are introduced below.

Integration within a single hospital considers modelling multiple departments or services within a single institution to understand their interdependencies. Integrated modelling remains narrow in scope, with most studies focusing on modelling operating theatres (Rachuba et al. 2024). For example, Heider et al. (2022) developed a master surgery schedule that incorporates capacity constraints in linked intensive care and recovery units. While many publications use simulation to model hospital EDs, relatively few consider the perspective of downstream hospital units. One of the recent exceptions is Oakley et al. (2020) who simulated multiple hospital wards in real-time to predict bed demand.

Links between a hospital and external services connect hospital operations with services such ambulance, primary care, and community care. Examples include Onen-Dumlu et al. (2022) who used DES to model flow between hospital and step-down intermediate community care and Abeysooriya et al. (2025) who used open-source UK NHS data to model the effect of delayed discharge on hospital operations.

Co-ordination across different hospitals describes modelling networks of multiple hospital facilities. Rutherford et al. (2022) simulated multi-hospital critical care networks in Canada, motivated by the high demand for these services during the COVID-19 pandemic. In the UK, Anagnostou et al. (2022) developed FACS-CHARM, a hybrid ABS and DES model to support COVID-19 management at a regional level. The hybrid approach used ABS to capture individual-level transmission dynamics and DES to model the partient flow and health service resource allocation. Harper & Mustafee (2019*b*) used the NHSquicker app to support urgent care networks, by using DES and forecasting to detect overcrowding ahead of time. This study shows how considering multiple hospitals in a region can be used to balance load.

Disease-specific pathways capture the patient journey across the full care pathway from diagnosis to rehabilitation. Brice et al. (2023) used a hybrid SD and ABS to model disease progression and treatment pathways for depression in Wales, capturing the impact of service capacity on disease. Other examples include Gjerloev et al. (2025) who developed a configurative 'Cancer Pathway Simulator' DES tool for modelling cancer pathways, and England et al. (2021) who used DES to model lung cancer pathways in Wales and experimented with scenarios to alleviate bottlenecks.

Population and policy-level integration simulation models go beyond individual healthcare organisations to incorporate population-level dynamics and the broader policy environment. The COVID-19 pandemic motivated a recent surge in studies using simulation to model pandemic response. Other examples include healthcare workforce planning e.g. Leerapan et al. (2021) used SD to address mismatches in health workforce supply and demand under Thailand's Universal Health Coverage and a SD study of neonatal health in Uganda (Semwanga et al. 2016) explored the impact of interventions such as community health education, incentive programs, and improvements in service delivery on reducing neonatal mortality.

5.2 The Importance of Integrated Modelling in Healthcare Systems

Integrated models are essential for capturing the complexity and interdependence inherent in healthcare systems. An integrated approach enables system-wide thinking and helps stakeholders make better decisions that reflect real-world complexity.

Simulation models that consider units of the health system in isolation and not in their wider context are unlikely to produce meaningful outputs. For example, a model that optimises ambulance-to-emergency department patient delivery is of limited practical value if the ED lacks the capacity to receive those patients. Similarly, accelerating hospital discharges through process optimisation will be unproductive unless appropriate capacity is available in community care facilities.

Integrated models are also needed to avoid spillover effects, where a change implemented in one component of the system indirectly impacts another component outside the model's focus. For example, Kim et al. (2024) studied data from 16 inpatient wards in a US hospital and found that increased utilisation in one inpatient unit can cause increased utilisation in other units the following day.

Occupancy management behaviours are an important modelling consideration, where healthcare units use strategies such as early discharges, patient boarding, or elective procedure cancellations to manage bed availability in a capacity constrained environment. These behaviours fundamentally alter the rules of a standard queueing system. Varney et al. (2019) highlight the presence of demand-driven discharge behaviours in Australia and New Zealand intensive care units. Their study demonstrates the inaccuracy of simulation model results when the occupancy management behaviours are not accounted for. Boyle & Bean (2024) also observed this issue in ED data. It is important to model individual units in their wider health system context.

5.3 Obstacles to the Development of Integrated Models in Healthcare Simulation

Data access is a major challenge to the development of integrated healthcare simulation models. Healthcare facilities often use disjoint electronic health record systems, typically designed for local operational needs, not for integrated use. Additionally, the data may use different coding systems and formats, which can make it difficult to link datasets for a patient across a health service. Further difficulty can arise with accessing multiple datasets across different services due to varying rules on data privacy and access.

Implementing healthcare simulation models is notoriously difficult, due to a range of technical and organisational barriers. Very few studies, even those focused on single hospital units, are successfully implemented in practice. Various reasons for this have been discussed, including limited stakeholder engagement, limited time and capacity, and cultural resistance. Integrated healthcare simulation models amplify these challenges and can introduce difficulty with competing interests and incentives from stakeholders in different areas – what is optimal for the system may not benefit individual healthcare units.

Developing integrated healthcare simulation models requires more time and effort than modelling individual units. This is due to a combination of factors, including the broader scope and increased model complexity, and the requirement for collaboration across multiple areas of the health service. Defining an appropriate level of detail for the simulation and avoiding increases in the model scope is also challenging in this context.

Robinson (2014) advocates for modellers to "build the simplest model possible to meet the objectives of the simulation study." Not all of the system needs to be represented in the same level of detail. Including the appropriate level of detail could reduce the obstacles to developing integrated models. For example, a model of operating theatres should model the flow of patients to downstream hospital beds. Instead of modelling the entire inpatient hospital in detail, the availability of downstream beds could be included using a simple distribution. Hybrid simulation methods and modular development are likely to play an important role here.

5.4 Challenges for Integrated Health System Simulation Modelling

Challenge IHS.1 Create simulation case-studies of successful integrated simulation models. These should demonstrate the value of linking datasets and the flow of patients across various components of hospitals and healthcare services.
Challenge IHS.2 Develop simulation models from an integrated perspective to avoid unintended spillover effects. For example, consider a hospital unit as a component of the wider hospital, a hospital as a component of a wider network of hospitals, and healthcare in the context of other services, such as primary care.
Challenge IHS.3 Use simulation to evaluate emerging approaches such as hospital at home, remote monitoring, and telehealth. Simulation should be used to determine their potential to reduce health system pressure and identify effective operational strategies.
Challenge IHS.4 Incorporate wider societal context (such as demographic trends, environmental factors, and economic conditions) into simulation models so they better reflect real-world system dynamics and inform more robust decision-making.
Challenge IHS.5 Design integrated simulation models with sufficient detail for meaningful decision support while remaining generalisable enough to be reused, updated, or adapted across different services and contexts.

6 Decision Support

Simulation models have two primary aims: to gain insights into the system being modelled and to support decision-making; for example by testing new policies or managing patient flow. This section explores the role of simulation as a decision-support tool for healthcare systems and outlines the grand challenges in this area.

6.1 Opportunities for Decision Support in Healthcare

Problem formulation is a critical aspect of successful healthcare simulation modelling. Often in healthcare simulation the stakeholder, or decision maker, is not a modeller themselves. Although they have a problem that needs solving, it can be ill-defined at the outset of a project. Building a model without a clear purpose for its use can lead to problems with model fidelity. Some model iteration should always be expected as a project progresses, but this can be somewhat avoided by starting from a point of common understanding and taking time over model formulation and objective setting.

The opportunity for impact using simulation in healthcare is vast. Highly impactful studies where simulation has been used for decision support working with NHS teams exist, e.g., Tuson et al. (2017) and Mustafee et al. (2024), but many academic projects fail to cross into impact and implementation. It is also often the case that efforts are focused on a local problem, without the resource to extend models for other localities (barriers to reproducibility), or a stand-alone model becomes outdated after changes are made to the system it was built for (barriers to reuse). To some extent model building using open science principles alleviates this issue, as we discuss in Section 3. By making model code openly available and written in freely available coding languages, other modellers should be able to pick up and modify/repurpose a model at lower cost and in a shorter time frame than building from scratch.

Simulation models can also be costly to build and often rely on commercial software. The advantage of using commercial software is that it can be user friendly and it often comes with visualisation capabilities, allowing a user to communicate the model logic to a client easily. Similar visualisation functionality is beginning to emerge in FOSS e.g. Vidigi provides animation for Ciw and Simpy[9]. However the expense of the software can be prohibitive for model sharing, and can be a barrier to the impact a model can achieve. This is before considering the practicalities of health service staff needing to download bespoke software onto their devices.

It is key for decision-support tools to evaluate the various consequences of decision alternatives, whether intended or unintended e.g., spillover effects to other hospital units. This is especially important when decision-making involves multiple stakeholders with different priorities and objectives, which is likely to be the case in healthcare.

Visualisation plays an important role in presenting clear insights that decision-makers can quickly interpret and act upon. Quantifying and communicating the uncertainty in simulation model outputs is also important, particularly for decision-makers who may prefer definitive recommendations. In the context of digital twins, speed is critical to ensuring that results are returned within a time window that allows the decision maker to take action. Decision alternatives should also be presented in an accessible and interpretable manner. A more detailed discussion of these aspects is included in Section 2.

6.2 Challenges for Decision Support and Healthcare Simulation

Challenge DS.1 Develop intuitive and explainable interfaces for simulation based decision-support. These should include clear and simple visualisations and display uncertainty.
Challenge DS.2 Explore how simulation can support decision-making among stakeholders who hold differing priorities and objectives. The aim is to provide a means for stakeholders to explore scenarios interactively and compare the consequences of different choices.

7 Including Human Behaviour

Incorporating human behaviour into simulation models has particular relevance in healthcare where many of the resources carrying out the activities in the model (nurses, doctors, healthcare specialists) are human and the model entities on whom the activities are being carried out (typically patients) are also human. When simulating patients' reactions to healthcare advice, human behaviour models are needed to dictate the population's willingness to comply, e.g., when modelling the effectiveness of screening (Brailsford et al. 2012) or strategies for reducing disease transmission (Rauner & Brandeau 2001). In systems where clinical decision-making is important for determining patient outcomes, human behaviour also becomes increasingly important, but this time the models focus on the behaviour of clinicians. There has been a growing interest in incorporating behavioural analysis into simulation models in recent years, and a recent review (Alwasel et al. 2025) reiterates the need for more research into developing accurate modelling of human behaviour, a conclusion that was previously suggested by Greasley (2016) and earlier still by Brailsford & Schmidt (2003). In particular there is a need for models that allow for feedback loops and learning. We split our discussion into three sections: staff and provider behaviour, patient and client behaviour, and social behaviour in public health.

7.1 Staff and Provider Behaviour

The behaviour of healthcare staff significantly influences system performance and patient outcomes. Staff decisions regarding resource allocation, patient prioritization, and clinical pathways are complex

[9] https://hsma-tools.github.io/vidigi/vidigi_docs

and context-dependent, shaped by experience, guidelines, and operational pressures.

ML offers powerful approaches to capture behavioural patterns from observational data. Allen et al. (2019) demonstrated this in stroke care, using random forests to model physician decision-making based on patient characteristics and geographical location, capturing nuanced variations in clinical practice and adherence to treatment guidelines that would be difficult to specify through traditional rule-based methods coded into the simulation logic. Similar approaches can be applied to blood-ordering behaviours, where clinicians' inventory management decisions affect supply chain efficiency (Dhahan et al. 2025, Dutta 2025), and operating room utilisation driven by staff decision-making rather than purely operational procedures and constraints (Fügener et al. 2017).

The modelling of staff behaviour using ML can now be integrated into many commercial simulation packages via calls to external libraries and tools. But arguably this integration is more natural and seamless in FOSS languages like Python and R, where native ML ecosystems already exist. These languages allow modellers to directly incorporate staff behaviour into simulation logic, using ML models trained on observational data, without requiring data export and import between separate software environments.

While the simulation technology and ML methods to incorporate staff behaviour exist, accessing appropriate observational data about staff behaviour and handling bias and data quality issues present significant ongoing challenges (Agniel et al. 2018, Ni et al. 2019). A common issue in simulation studies is missing, incomplete, or poor logging of data (Perets et al. 2025), largely due to the process data requirements of simulation clashing with the clinical nature of data collection in healthcare. Another common problem is that the decision-making data may not reflect the intended process or ideal decision for patients, but rather the activity that happened as staff adapt to operational pressures. The result is that developing robust models of staff behaviour often requires substantial additional data collection and analysis beyond the core simulation project, adding time and complexity to modelling efforts.

7.2 Patient and Client Behaviour

Patient behaviour influences and is influenced by the healthcare system through mechanisms such as adherence, preferences, and responses to system pressures.

Patient adherence has different dimensions, including medication, self-monitoring, and screening (Kılıç & Güneş 2024). Adherence is important for patients because it directly affects disease outcomes and prognosis. It also has a direct impact on the healthcare system, for example through missed appointments and preventable hospital admissions. Brailsford et al. (2012) used regression to predict the likelihood of attendance at breast cancer screening appointments under two different psychological models. These behavioural predictions were incorporated as psychological parameters within a DES model of a UK breast cancer screening service. The simulation showed that improving appointment attendance could be as effective as increasing screening frequency, demonstrating that patient adherence behaviour can substantially influence system level outcomes. Pereira et al. (2024) used ABS to investigate adherence to diabetic retinopathy screening in Portugal. Patient adherence behaviour was modelled using a combination of logistic regression and fuzzy logic, and the simulation demonstrated a reasonable level of accuracy when validated against administrative data. ML has also been used by Ferro et al. (2020) to predict no-show behaviour of patients at medical appointments in Colombia. This work could be embedded in a simulation model to experiment with strategies for reducing no-show behaviour.

Patient behaviour can also be influenced by healthcare system pressures; for example, crowding in EDs is associated with an increased risk of patients leaving without being seen (Gorski et al. 2021). This can create unintended consequences, such as patients returning to hospital with a potential deterioration in their condition (Roby et al. 2022). Gartner & Padman (2020) used ML to identify factors influencing patients' perceptions of ED waiting times and incorporated these factors into a DES model to test strategies for improving patient satisfaction.

Healthcare delivery is affected by patient preferences. NHS England data has shown that discharge delays due to 'patient or family choice' accounted for 11% of all delayed bed days between 2010-2020 (The King's Fund 2023). Xu et al. (2008) used ABS to model the co-ordination between hospitals and community care facilities, incorporating patient behaviour by using a preference function derived from experience. Smith et al. (2018) employed discrete choice modelling to analyse patient's hospital selection patterns using administrative data, showing that travel distance was the strongest determinant of hospital choice. This paper presents a statistical method for quantifying patient choice behaviour, which could be integrated into simulation models.

The balance between fairness and equity in human behaviour is present in many healthcare settings. Osório (2017) proposed a resource allocation rule for situations where both self-interest and equity (fairness) are important that could be used within healthcare simulation. Equity is further discussed in Section 8.

Including human behaviour in healthcare simulation models is important to capture the relationship between patient behaviour and healthcare system dynamics, and for producing more accurate representations of healthcare systems. The papers discussed throughout this section illustrate various methods such as psychological behaviour models, discrete choice modelling, and ML. A major obstacle for including patient behaviour in healthcare simulations is a lack of data, which often needs to be collected using targeted surveys, e.g. Gartner & Padman (2020). Data limitations also create challenges with model validation, as simulation outputs cannot be directly compared to observed healthcare system data.

7.3 Social Behaviour in Public Health

Incorporating human behaviour into simulation models for public health studies requires both suitable data and an appropriate way of modelling the behaviour and its impact on the entities within the model. For example, ABS is frequently used in the modelling of infectious diseases, allowing individual behaviour to be taken into account. Rodriguez-Cartes et al. (2024) used a health belief model (HBM) to describe the likelihood of people wearing a mask during the COVID-19 pandemic. The HBM was fitted to survey data collected by MIT and Facebook (Collis et al. 2022), which measured people's beliefs and perceptions in relation to COVID-19 and also self-reported mask usage. Similar ideas are also important when working with other public health crises, e.g., the opioid crisis (Cerdá et al. 2021, Brandeau 2023) and homelessness (Knerich et al. 2019).

As identified by Bedson et al. (2021), key among the challenges for modellers is the need to develop modelling protocols to incorporate human behaviour. This is echoed by Hill et al. (2024) who highlight the need to balance interpretability with complexity. They discuss the benefits of simple models in achieving this.

Data and its interpretation is also a challenge. Research within social science does not tend to produce quantitative models of reactions, as needed by simulation modellers. Funk et al. (2010) suggest that more observational studies are needed to enable parameterisation of human behaviour in models, but are also positive that improved technology makes it easier to carry these out. The study of COVID-19 behaviours described above (Collis et al. 2022), which surveyed participants in 67 countries and included over 2 million responses, is a good example of how technology can help with developing useful datasets for modellers. As recommended in Bedson et al. (2021), in order to achieve the gains in understanding associated with incorporating human behaviour in models, there is a need to improve inter-disciplinary working between social scientists and modellers. This could include the co-design of data-collection protocols, and education specific to those working on the borderline between these two areas.

7.4 Challenges for Including Human Behaviour

Challenge HB.1 Develop a set of processes for incorporating ML modelling of human behaviour into hybrid simulation models of healthcare systems.
Challenge HB.2 Produce frameworks that capture the appropriate level of detail when modelling systems where human behaviour is important; particularly in ABS for public health, including modelling of infectious diseases.
Challenge HB.3 Integrate qualitative and quantitative studies of human behaviour into simulation models.

8 Equity and Health Inequality

Access to healthcare is a fundamental human right. Yet, health inequality is persistent in society and often tied to socio-economic marginalization. Healthcare systems are under increasing pressure to balance increasing demand with resource constraints in an equitable manner. Simulation can help providers and operations managers visualise the equity implications of operations and policy decisions from different perspectives. Making equitable decisions often requires understanding trade-offs between competing objectives. Multi-objective simulation optimisation allows us to quantify these trade-offs.

8.1 What is Equity?

Equity is a notion of fairness or justice that has no standard definition (Dhahan et al. 2023). Some of the more common concepts include: utilitarianism, horizontal equity, vertical equity, proportional equity, and min-max equity. It depends on context which definition of equity is most appropriate and it is important to understand the equity implication of any modelling assumptions that we might make.

Utilitarianism is a notion of equity in which resources are allocated to obtain maximum utility or benefit (Bertsimas et al. 2011). Horizontal equity (Epstein et al. 2007) is the notion that groups in the same circumstances should have similar access to resources. Vertical equity (Breugem & Van Wassenhove 2022) is the notion that groups in different circumstances should have different access to resources. Proportional equity (Bertsimas et al. 2011) involves the distribution of resources to a group in proportion to some definition of the worth of each member in the group. Max-min (Min-max) equity (Bertsimas et al. 2011) corresponds to finding an allocation of resources to a group such that trying to increase (decrease) the utility of any group member results in a decrease (increase) in the utility among group members with equal or lesser (greater) utility.

8.2 Equity in Healthcare Simulation

The nature of healthcare requires that we pay close attention to equity in using simulation models to inform decisions. Frequently, there are constraints in the availability of resources due to budget or other limitations (Guindo et al. 2012, Lane et al. 2017, Wang & Demeulemeester 2023), geographical challenges in some jurisdictions (Wu et al. 2007), and the need for timely access to care (Kuo et al. 2023). During public health crises (Brandeau et al. 2003, Yin et al. 2023) or natural disasters (Cao

& Huang 2012) these considerations come to the fore; however, they are ever present within the healthcare system.

The COVID-19 Pandemic put considerable stress on the healthcare system worldwide (Currie et al. 2020). Simulation played an important role in the planning of case projections, access to mechanical ventilators (Day et al. 2020, Yin et al. 2023, Zimmerman et al. 2023), distribution of personal protective equipment, allocation of beds, and distribution of vaccines (Enayati & Özaltın 2020, Breugem & Van Wassenhove 2022). The extensive use of simulation modelling to inform the public response to the COVID-19 pandemic highlighted the need for a better understanding of how we capture equity in simulation models and the risk of implicit inequity in our modelling assumptions.

The combination of limited supply, perishability, and the life-saving nature of blood products and organs creates particular challenges for equitable distribution of these products (Yuan et al. 1994, Zenios et al. 2000, Kenan & Diabat 2022, Bertsimas et al. 2013). Simulation studies have been used to evaluate inventory practices and distribution networks, but decision-making often requires balancing cost-effectiveness, robustness, and fairness considerations. This can present unique challenges for simulation models, especially in the context of simulation optimisation (Fariman et al. 2024).

Equitable access to care is an important consideration in reducing health inequalities. People who are socio-economically marginalised, including people who are homeless, indigenous populations in many countries, racial minorities, and people with mental health or substance use issues are often marginalised from the healthcare system. Simulation has been used to study equitable access to HIV treatment (Earnshaw et al. 2007, Cleary et al. 2010). Demir et al. (2024) developed the SimulEQUITY framework to model health inequality in hospital access. Equity considerations also arise in using simulation to model the location of healthcare services or facilities (Bak 2022). A more equitable healthcare system should balance access to care for patients with fair staffing models for providers. Healthcare providers are often overworked and there are shortages in some areas (Cunningham & Gonzalez-Guarda 2023, Santric Milicevic et al. 2024).

Incorporating equity in simulation models naturally leads to balancing competing objectives through multi-objective simulation optimisation. Different notions of equity and fairness correspond to different objective functions. Exploring the implications of these different modelling assumptions is important to understand how equity is being represented—or failing to be represented—in our simulation models (Xinying Chen & Hooker 2023, Dieckmann & Nirula 2024).

8.3 Challenges for Equity in Healthcare Simulation

Challenge E.1 Use simulation to gain a better understanding of the nuances of different notions of equity and how this affects the use of simulation in healthcare resources planning and policy development.

Challenge E.2 Improve the efficiency of multi-objective simulation optimisation solvers and refine methods for presenting results so that the trade-offs can be easily understood by decision-makers. Addressing equity typically results in multi-objective optimisation problems and these have associated computational challenges but also difficulties in communicating ideas such as Pareto fronts to decision-makers.

Challenge E.3 Assessment of how the application of ML and AI within simulation models affects equity. (Not introducing bias from training on inequitable data).

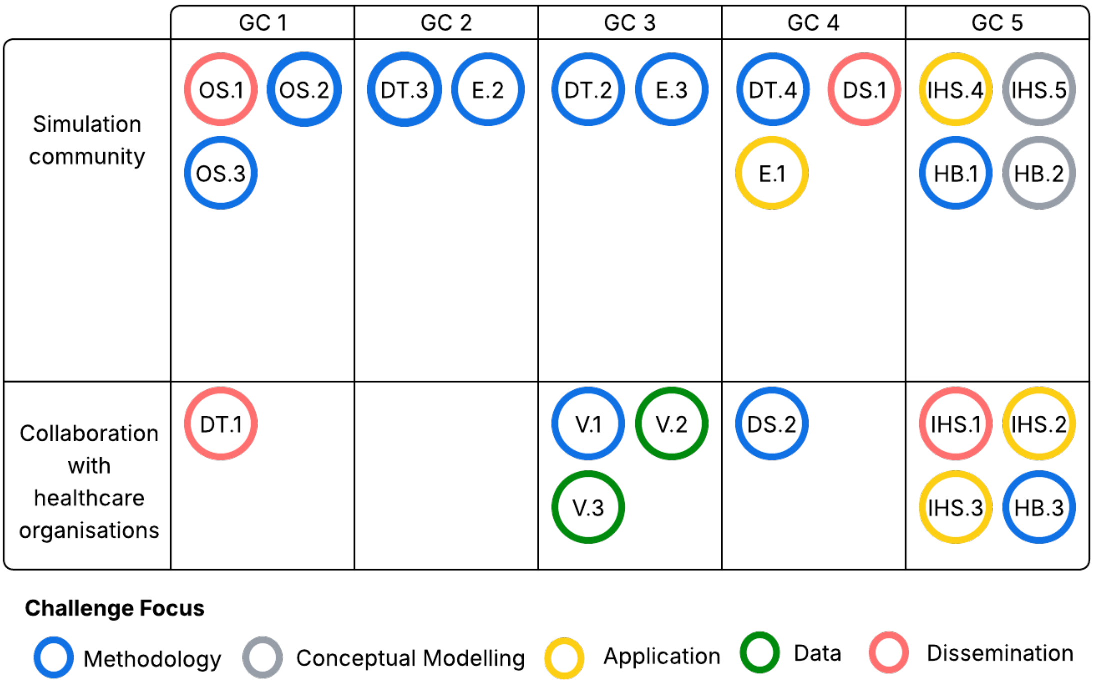

Figure 1: Summary of challenges

9 Conclusion

Several common ideas emerge from the challenges identified in each of the seven themes. Most prevalent is the need to publish high-impact case studies of simulation models. We do not include this as a grand challenge but instead highlight the fact that in healthcare M&S, case studies are the best means of getting work widely used as they demonstrate how new methodology can be applied in a healthcare setting. The delivery of healthcare is also changing, with a move to more personalised medicine, the increased use of robotics, a greater focus on prevention, and a desire to move more care back into communities or even patients' homes (Department of Health and Social Care 2025). These changes, combined with the opportunities of greater access to real-time data feeds and the challenges of increased demand due to ageing populations and climate change, mean that there will be demand for simulation modelling of systems that look very different from the traditional hospital simulations in use today. Again, we do not include this as a grand challenge but more as business as usual for healthcare M&S researchers, who are accustomed to modelling new systems as they arise.

Figure 1 summarises the challenges from each of the seven themes, linking them to the five grand challenges listed below and categorising them based on whether they are challenges solely for the simulation community or in collaboration with healthcare professionals. While the majority are methodological challenges for the simulation community, the challenges from the theme on improving the integration of the health system are more around application and dissemination. Challenges for healthcare organisations collaborating with the simulation community include validation and data but also some work around application and dissemination of results and models.

We conclude the article by listing our five grand challenges for healthcare simulation.

1. Develop methods, tools and training to reduce the barriers to both creating and implementing reusable simulation models within healthcare.
2. Improve the efficiency of simulation optimisation algorithms so that they can produce good-enough solutions fast enough to be used for operational decision-making.
3. Develop validation methods for digital twin simulations that are robust to errors in input data and highlight where more data are needed.
4. Determine best practice for decision support tools that enable equitable decision-making under constrained resources via a simulation model.
5. Produce frameworks that capture the bigger picture with the appropriate level of detail where either one or both of human behaviour and interactions with the wider health system and environment are important.

While important for healthcare simulation, these grand challenges are not exclusive to modelling healthcare. What is perhaps specific to healthcare is the need to sell the modelling to multiple different system users: administrative staff, clinical staff, patients and politicians. This means that healthcare simulation needs to be clearly documented, easy to explain, and to be proven to work.

References

21st Century Grand Challenges (n.d.), `https://obamawhitehouse.archives.gov/administration/eop/ostp/grand-challenges`. Accessed on October 17 2021.

Abbasi, A. B., Layden, J., Gordon, W., Gregurick, S., DeLew, N., Grossman, J., Bierman, A. S., Monarez, S., Curtis, L. H., Viall, A. H., Rocca, M., Rivera, D. R., Marston, H., Mugge, A., Smith, S. R., Bent, K., Macrae, J., Sheehy, A., Wegrzyn, R. D., Valdez, R. B., Johnson, C., Bush, L., Blum, J., Cohen, M. K., Bertagnolli, M. M., Califf, R. M. & Tripathi, M. (2025), 'A unified approach to health data exchange: A report from the us dhhs', *JAMA* **333**(12), 1074. doi:http://dx.doi.org/10.1001/jama.2025.0068.

Abeysooriya, R. P., Amarasinghe, N., Boyle, L., Currie, C. S. & Lamas-Fernandez, C. (2025), Simulation modelling of delayed discharge from hospital, *in* 'Proceedings of the Operational Research Society Simulation Workshop'. doi:https://doi.org/10.36819/SW25.040.

Agniel, D., Kohane, I. S. & Weber, G. M. (2018), 'Biases in electronic health record data due to processes within the healthcare system: retrospective observational study', *BMJ* **361**, k1479. doi:https://doi.org/10.1136/bmj.k1479.

Allen, C. & Mehler, D. M. (2019), 'Open science challenges, benefits and tips in early career and beyond', *PLoS biology* **17**(5), e3000246. doi:https://doi.org/10.1371/journal.pbio.3000246.

Allen, M., Pearn, K., Monks, T., Bray, B. D., Everson, R., Salmon, A., James, M. & Stein, K. (2019), 'Can clinical audits be enhanced by pathway simulation and machine learning? an example from the acute stroke pathway', *BMJ Open* **9**(9). doi:https://doi.org/10.1136/bmjopen-2018-028296.

Alwasel, A., Fakhimi, M., Mustafee, N. & Stergioulas, L. (2025), 'Modeling and simulation for behavioral analysis in healthcare: A review', *ACM Transactions on Modeling and Computer Simulation* **36**, 1–21. doi:https://doi.org/10.1145/3742428.

Anagnostou, A., Groen, D., Taylor, S. J., Suleimenova, D., Abubakar, N., Saha, A., Mintram, K., Ghorbani, M., Daroge, H., Islam, T. et al. (2022), FACS-CHARM: a hybrid agent-based and discrete-event simulation approach for Covid-19 management at regional level, *in* '2022 Winter Simulation Conference (WSC)', IEEE, pp. 1223–1234. doi:https://doi.org/10.1109/WSC57314.2022.10015462.

Bak, M. A. (2022), 'Computing fairness: ethics of modeling and simulation in public health', *Simulation* **98**(2), 103–111. https://doi.org/10.1177/0037549720932656.

Bedson, J., Skrip, L., Pedi, D., Abramowitz, S., Carter, S., Jalloh, M., Funk, S., Gobat, N., Giles-Vernick, T., Chowell, G., de Almeida, J., Elessawi, R., Scarpino, S., Hammond, R., Briand, S., Epstein, J., Hebert-Dufresne, L. & Althouse, B. (2021), 'A review and agenda for integrated disease models including social and behavioural factors', *Nature Human Behaviour* **5**, 834–846. doi:https://doi.org/10.1038/s41562-021-01136-2.

Beliën, J., Brailsford, S., Demeulemeester, E., Demirtas, D., Hans, E. W. & Harper, P. (2025), 'Fifty years of operational research applied to healthcare', *European Journal of Operational Research* **326**(2), 189–206. doi:https://doi.org/10.1016/j.ejor.2024.12.040.

Bertsimas, D., Farias, V. F. & Trichakis, N. (2011), 'The price of fairness', *Operations Research* **59**(1), 17–31. doi:https://doi.org/10.1287/opre.1100.0865.

Bertsimas, D., Farias, V. F. & Trichakis, N. (2013), 'Fairness, efficiency, and flexibility in organ allocation for kidney transplantation', *Operations Research* **61**(1), 73–87. doi:https://doi.org/10.1287/opre.1120.1138.

Biller, B., Jiang, X., Yi, J., Venditti, P. & Biller, S. (2022), Simulation: the critical technology in digital twin development, *in* 'Proceedings of the 2022 Winter Simulation Conference', IEEE, IEEE, pp. 1340–1355. doi: https://doi.org/10.1109/WSC57314.2022.10015246.

Bitencourt, J., Wooley, A. & and, G. H. (2025), 'Verification and validation of digital twins: a systematic literature review for manufacturing applications', *International Journal of Production Research* **63**(1), 342–370. doi: https://doi.org/10.1080/00207543.2024.2357741.

Boyle, L. & Bean, N. (2024), Dependence between arrival and service processes in healthcare simulation modelling, *in* '2024 Winter Simulation Conference (WSC)', IEEE, pp. 918–927. doi:https://doi.org/10.1109/WSC63780.2024.10838887.

Brailsford, S. C., Eldabi, T., Kunc, M., Mustafee, N. & Osorio, A. F. (2019), 'Hybrid simulation modelling in operational research: A state-of-the-art review', *European Journal of Operational Research* **278**(3), 721–737. doi:https://doi.org/10.1016/j.ejor.2018.10.025.

Brailsford, S. C., Harper, P. R. & Sykes, J. (2012), 'Incorporating human behaviour in simulation models of screening for breast cancer', *European Journal of Operational Research* **219**(3), 491–507. doi: https://doi.org/10.1016/j.ejor.2011.10.041.

Brailsford, S. & Schmidt, B. (2003), 'Towards incorporating human behaviour in models of health care systems: An approach using discrete event simulation', *European journal of operational research* **150**(1), 19–31. doi:https://doi.org/10.1016/S0377-2217(02)00778-6.

Brandeau, M. L. (2023), 'Responding to the US opioid crisis: leveraging analytics to support decision making', *Health care management science* **26**(4), 599–603. doi:https://doi.org/10.1007/s10729-023-09657-0.

Brandeau, M., Zaric, G. & Richter, A. (2003), 'Resource allocation for control of infectious diseases in multiple independent populations: beyond cost-effectiveness analysis', *Health Economics* **22**(4), 575–598. doi:https://doi.org/10.1016/S0167-6296(03)00043-2.

Breugem, T. & Van Wassenhove, L. N. (2022), 'The price of imposing vertical equity through asymmetric outcome constraints', *Management Science* **68**(11), 7977–7993. doi:https://doi.org/10.1287/mnsc.2021.4287.

Brice, S. N., Harper, P. R., Gartner, D. & Behrens, D. A. (2023), 'Modeling disease progression and treatment pathways for depression jointly using agent based modeling and system dynamics', *Frontiers in Public Health* **10**, 1011104. doi:https://doi.org/10.3389/fpubh.2022.1011104.

Brown, T. B., Mann, B., Ryder, N., Subbiah, M., Kaplan, J., Dhariwal, P., Neelakantan, A., Shyam, P., Sastry, G., Askell, A., Agarwal, S., Herbert-Voss, A., Krueger, G., Henighan, T., Child, R., Ramesh, A., Ziegler, D. M., Wu, J., Winter, C., Hesse, C., Chen, M., Sigler, E., Litwin, M., Gray, S., Chess, B., Clark, J., Berner, C., McCandlish, S., Radford, A., Sutskever, I. & Amodei, D. (2020), 'Language models are few-shot learners'.
URL: *https://arxiv.org/abs/2005.14165*

Cao, H. & Huang, S. (2012), 'Principles of scarce medical resource allocation in natural disaster relief: A simulation approach', *Medical Decision Making* **32**(3), 470–476. doi:https://doi.org/10.1177/0272989X12437247.

Cerdá, M., Jalali, M. S., Hamilton, A. D., DiGennaro, C., Hyder, A., Santaella-Tenorio, J., Kaur, N., Wang, C. & Keyes, K. M. (2021), 'A systematic review of simulation models to track and address the opioid crisis', *Epidemiologic reviews* **43**(1), 147–165. doi:https://doi.org/10.1093/epirev/mxab013.

Cleary, S., Mooney, G. & McIntyre, D. (2010), 'Equity and efficiency in hiv-treatment in south africa: The contribution of mathematical programming to priority setting', *Health Economics* **19**(10), 1166–1180. doi:https://doi.org/10.1002/hec.1542.

Collis, A., Garimella, K., Moehring, A., Rahimian, M. A., Babalola, S., Gobat, N. H., Shattuck, D., Stolow, J., Aral, S. & Eckles, D. (2022), 'Global survey on covid-19 beliefs, behaviours and norms', *Nature Human Behaviour* **6**, 1310–1317. doi:https://doi.org/10.1038/s41562-022-01347-1.

Cunningham, T. & Gonzalez-Guarda, R. M. (2023), Burned out on burnout—the urgency of equity-minded structural approaches to support nurses, *in* 'JAMA Health Forum', Vol. 4, American Medical Association, pp. e235249–e235249. doi:https://doi.org/10.1001/jamahealthforum.2023.5249.

Currie, C. S., Fowler, J. W., Kotiadis, K., Monks, T., Onggo, B. S., Robertson, D. A. & Tako, A. A. (2020), 'How simulation modelling can help reduce the impact of covid-19', *Journal of Simulation* **14**(2), 83–97. doi:https://doi.org/10.1080/17477778.2020.1751570.

Dagkakis, G. & Heavey, C. (2016), 'A review of open source discrete event simulation software for operations research', *Journal of Simulation* **10**(3), 193–206. doi:https://doi.org/10.1057/jos.2015.9.

Dagstuhl, S. (2002), 'Grand challenges for modelling and simulation', Available at `www.dagstuhl.de/02351`. Accessed on October 1 2022.

Day, R. T., Guidry, B. S., Drolet, B. C. & Clayton, E. W. (2020), 'From ventilators to vaccines: Reframing the ethics of resource allocation', *The American Journal of Bioethics* **20**(7), W15–W16. doi:https://doi.org/10.1080/15265161.2020.1782530.

Demir, E., Yakutcan, U. & Page, S. (2024), 'Using simulation modelling to transform hospital planning and management to address health inequalities', *Social Science & Medicine* **347**, 116786. doi:https://doi.org/10.1016/j.socscimed.2024.116786.

den Eynden, V. V., Knight, G., Vlad, A., Radler, B., Tenopir, C., Leon, D., Manista, F., Whitworth, J. & Corti, L. (2016), Survey of wellcome researchers and their attitudes to open research, Project report, Wellcome Trust, London. doi:https://doi.org/10.6084/m9.figshare.4055448.

Department of Health and Social Care (2025), Fit for the future: 10 year health plan for england. CP 1350; Crown copyright 2025. Accessed on 13 February 2026. `https://assets.publishing.service.gov.uk/media/6888a0b1a11f859994409147/fit-for-the-future-10-year-health-plan-for-england.pdf`.

Dhahan, J., Morrison, D., Shih, A. W., McDonald, D., Chen, R., Hao, L., Rosinski, K., Buchko, S., Blake, J. & Rutherford, A. (2025), 'Red blood cell inventory management: Insights from transfusion laboratory technologists in British Columbia, Canada', *Transfusion Medicine* **35**(2), 116–124. doi:https://doi.org/10.1111/tme.13131.

Dhahan, J., Rutherford, A., Shih, A., Li, N. & Down, D. (2023), Equitable allocation of scarce resources during the covid-19 pandemic: A case study for convalescent plasma distribution, *in* 'Proceedings of the 2023 Winter Simulation Conference', IEEE, pp. 982–993. doi:https://doi.org/10.1109/WSC60868.2023.10408073.

Dieckmann, P. & Nirula, L. (2024), 'Moving towards deep equity, diversity, inclusivity and accessibility in simulation: a call to explore the promises and perils', *Advances in Simulation* **9**(1), 6. doi:https://doi.org/10.1186/s41077-024-00278-3.

Dutta, P. (2025), Blood Supply Chain Networks in Healthcare: Game Theory Models and Numerical Case Studies, PhD thesis, University of Massachusetts, Amherst. doi:https://doi.org/10.7275/14217613.

Earnshaw, S. R., Hicks, K., Richter, A. & Honeycutt, A. (2007), 'A linear programming model for allocating hiv prevention funds with state agencies: A pilot study.', *Health Care Management Science* **10**(3), 239–252. doi:https://doi.org/10.1007/s10729-007-9017-8.

Eddy, D. M., Hollingworth, W., Caro, J. J., Tsevat, J., McDonald, K. M. & Wong, J. B. (2012), 'Model Transparency and Validation: A Report of the ISPOR-SMDM Modeling Good Research Practices Task Force–7', *Medical Decision Making* **32**(5), 733–743. doi:https://doi.org/10.1177/0272989X12454579.

Enayati, S. & Özaltın, O. Y. (2020), 'Optimal influenza vaccine distribution with equity', *European Journal of Operational Research* **283**(2), 714–725. doi:https://doi.org/10.1016/j.ejor.2019.11.025.

England, T. J., Harper, P. R., Crosby, T., Gartner, D., Arruda, E. F., Foley, K. G. & Williamson, I. J. (2021), 'Examining the diagnostic pathway for lung cancer patients in wales using discrete event simulation', *Translational Lung Cancer Research* **10**(3), 1368. doi:https://doi.org/10.21037/tlcr-20-919.

Epstein, D. M., Chalabi, Z., Claxton, K. & Sculpher, M. (2007), 'Efficiency, equity, and budgetary policies: Informing decisions using mathematical programming', *Medical Decision Making* **27**(2), 128–137. doi:https://doi.org/10.1177/0272989X06297396.

Fariman, S. K., Danesh, K., Pourtalebiyan, M., Fakhri, Z., Motallebi, A. & Fozooni, A. (2024), ‘A robust optimization model for multi-objective blood supply chain network considering scenario analysis under uncertainty: a multi-objective approach’, *Scientific Reports* **14**(1), 9452. doi:https://doi.org/10.1038/s41598-024-57521-0.

Ferro, D. B., Brailsford, S., Bravo, C. & Smith, H. (2020), ‘Improving healthcare access management by predicting patient no-show behaviour’, *Decision Support Systems* **138**, 113398. doi:https://doi.org/10.1016/j.dss.2020.113398.

Fügener, A., Schiffels, S. & Kolisch, R. (2017), ‘Overutilization and underutilization of operating rooms-insights from behavioral health care operations management’, *Health care management science* **20**(1), 115–128. doi:https://doi.org/10.1007/s10729-015-9343-1.

Funk, S., Salathe, M. & Jansen, V. (2010), ‘Modelling the influence of human behaviour on the spread of infectious diseases: a review’, *J R Soc Interface* **7**, 1247 – 1256. doi:https://doi.org/10.1098/rsif.2010.0142.

Gartner, D. & Padman, R. (2020), ‘Machine learning for healthcare behavioural or: Addressing waiting time perceptions in emergency care’, *Journal of the Operational Research Society* **71**(7), 1087–1101. doi:https://doi.org/10.1080/01605682.2019.1571005.

Gjerloev, A., Impelluso, G., Grieco, L., Jani, Y., Pagel, C. & Crowe, S. (2025), ‘A configurable discrete event simulation to model patient flow along cancer pathways’, *Journal of the Operational Research Society* pp. 1–19. doi:https://doi.org/10.1080/01605682.2025.2557921.

Goldacre, B. & Morley, J. (2022), ‘Better, broader, safer: Using health data for research and analysis’. A review commissioned by the Secretary of State for Health and Social Care, Department of Health and Social Care. Accessed on February 13 2026. `https://assets.publishing.service.gov.uk/media/624ea0ade90e072a014d508a/goldacre-review-using-health-data-for-research-and-analysis.pdf`.

Gomes, D. G., Pottier, P., Crystal-Ornelas, R., Hudgins, E. J., Foroughirad, V., Sánchez-Reyes, L. L., Turba, R., Martinez, P. A., Moreau, D., Bertram, M. G. et al. (2022), ‘Why don’t we share data and code? perceived barriers and benefits to public archiving practices’, *Proceedings of the Royal Society B* **289**(1987), 20221113. doi:https://doi.org/10.1098/rspb.2022.1113.

Gorski, J. K., Arnold, T. S., Usiak, H. & Showalter, C. D. (2021), ‘Crowding is the strongest predictor of left without being seen risk in a pediatric emergency department’, *The American journal of Emergency Medicine* **48**, 73–78. doi:https://doi.org/10.1016/j.ajem.2021.04.005.

Greasley, A. (2016), Methods of modelling people using discrete-event simulation, *in* ‘2016 6th International Conference on Simulation and Modeling Methodologies, Technologies and Applications (SIMULTECH)’, IEEE, pp. 1–6. doi:https://doi.org/10.5220/0006005803120317.

Grimm, V., Berger, U., Bastiansen, F., Eliassen, S., Ginot, V., Giske, J., Goss-Custard, J., Grand, T., Heinz, S. K., Huse, G., Huth, A., Jepsen, J. U., Jørgensen, C., Mooij, W. M., Müller, B., Pe’er, G., Piou, C., Railsback, S. F., Robbins, A. M., Robbins, M. M., Rossmanith, E., Rüger, N., Strand, E., Souissi, S., Stillman, R. A., Vabø, R., Visser, U. & DeAngelis, D. L. (2006), ‘A standard protocol for describing individual-based and agent-based models’, *Ecological Modelling* **198**(1), 115–126. doi:https://doi.org/10.1016/j.ecolmodel.2006.04.023.

Grimm, V., Berger, U., DeAngelis, D. L., Polhill, J. G., Giske, J. & Railsback, S. F. (2010), 'The odd protocol: A review and first update', *Ecological Modelling* **221**(23), 2760–2768. doi:https://doi.org/10.1016/j.ecolmodel.2010.08.019.

Grimm, V., Railsback, S. F., Vincenot, C. E., Berger, U., Gallagher, C., DeAngelis, D. L., Edmonds, B., Ge, J., Giske, J., Groeneveld, J., Johnston, A. S., Milles, A., Nabe-Nielsen, J., Polhill, J. G., Radchuk, V., Rohwäder, M.-S., Stillman, R. A., Thiele, J. C. & Ayllón, D. (2020), 'The odd protocol for describing agent-based and other simulation models: A second update to improve clarity, replication, and structural realism', *Journal of Artificial Societies and Social Simulation* **23**(2), 7. doi:https://doi.org/10.18564/jasss.4259.

Guindo, L. A., Wagner, M., Baltussen, R., Rindress, D., van Til, J., Kind, P. & Goetghebeur, M. M. (2012), 'From efficacy to equity: Literature review of decision criteria for resource allocation and healthcare decisionmaking', *Cost Effectiveness and Resource Allocation* **10**(1), 1–13. doi:https://doi.org/10.1186/1478-7547-10-9.

Haim, A., Shaw, S. T. & Heffernan, N. T. (2023), How to open science: promoting principles and reproducibility practices within the artificial intelligence in education community, *in* 'International Conference on Artificial Intelligence in Education', Springer, pp. 74–78. doi:https://doi.org/10.1007/978-3-031-36336-$8_1$1.

Harper, A., Monks, T. & Manzi, S. (2023), 'Deploying healthcare simulation models using containerization and continuous integration'.
URL: *osf.io/qez45*

Harper, A. & Mustafee, N. (2019*a*), A hybrid modelling approach using forecasting and real-time simulation to prevent emergency department overcrowding, *in* 'Proceedings of the 2019 Winter Simulation Conference (WSC)', pp. 1208–1219. doi:https://doi.org/10.1109/WSC40007.2019.9004862.

Harper, A. & Mustafee, N. (2019*b*), A hybrid modelling approach using forecasting and real-time simulation to prevent emergency department overcrowding, *in* 'Proceedings of the 2019 Winter Simulation Conference (WSC)', IEEE, pp. 1208–1219. doi:https://doi.org/10.1109/WSC40007.2019.9004862.

Harper, A., Mustafee, N. & Pitt, M. (2023), 'Increasing situation awareness in healthcare through real-time simulation', *Journal of the Operational Research Society* **74**(11), 2339–2349. doi:https://doi.org/10.1080/01605682.2022.2147030.

Harvard, S., Adibi, A., Easterbrook, A., Werker, G. R., Murphy, D., Grant, D., Mclean, A., Majdzadeh, Z. & Sadatsafavi, M. (2022), 'Developing an online infrastructure to enhance model accessibility and validation: The peer models network', *PharmacoEconomics* **40**(10), 1005–1009. doi:https://doi.org/10.1007/s40273-022-01179-x.

Heather, A., Monks, T., Harper, A., Mustafee, N. & Mayne, A. (2025), 'On the reproducibility of discrete-event simulation studies in health research: an empirical study using open models', *Journal of Simulation* **0**(0), 1–25. doi:https://doi.org/10.1080/17477778.2025.2552177.

Heib, A. R., Currie, C. S., Onggo, B. S., Smith, H. K. & Kerr, J. (2023), A generalized symbiotic simulation model of an emergency department for real-time operational decision-making, *in* 'Proceedings of the 2023 Winter Simulation Conference', pp. 1042–1053. doi:https://doi.org/10.1109/WSC60868.2023.10407981.

Heider, S., Schoenfelder, J., Koperna, T. & Brunner, J. O. (2022), ‘Balancing control and autonomy in master surgery scheduling: benefits of icu quotas for recovery units’, *Health Care Management Science* **25**(2), 311–332. doi:https://doi.org/10.1007/s10729-021-09588-8.

Hill, E. M., Ryan, M., Haw, D., Lynch, M. P., McCabe, R., Milne, A. E., Turner, M. S., Vedhara, K., Zeng, F., Barons, M. J., Nixon, E. J., Parnell, S. & Bolton, K. J. (2024), ‘Integrating human behaviour and epidemiological modelling: unlocking the remaining challenges’, *Mathematics in Medical and Life Sciences* **1**(1), 2429479. doi:https://doi.org/10.1080/29937574.2024.2429479.

Hoot, N. R., LeBlanc, L. J., Jones, I., Levin, S. R., Zhou, C., Gadd, C. S. & Aronsky, D. (2008), ‘Forecasting emergency department crowding: A discrete event simulation’, *Annals of Emergency Medicine* **52**(2), 116 – 125. doi:https://doi.org/10.1016/j.annemergmed.2007.12.011.

Hrynaszkiewicz, I., Harney, J. & Cadwallader, L. (2021), ‘A survey of code sharing practice and policy in computational biology’, OSF Preprints. doi:https://doi.org/10.31219/osf.io/f73a6.

Janssen, M. A., Alessa, L. N., Barton, M., Bergin, S. & Lee, A. (2008), ‘Towards a community framework for agent-based modelling’, *Journal of Artificial Societies and Social Simulation* **11**(2), 6. **URL:** *http://jasss.soc.surrey.ac.uk/11/2/6.html*

Janssen, M. A., Pritchard, C. & Lee, A. (2020), ‘On code sharing and model documentation of published individual and agent-based models’, *Environmental Modelling & Software* **134**, 104873. doi:https://doi.org/10.1016/j.envsoft.2020.104873.

Kar, E., Eldabi, T. & Fakhimi, M. (2022), Hybrid simulation in healthcare: A review of the literature, *in* ‘Proceedings of the 2022 Winter Simulation Conference (WSC)’, pp. 1211–1222. doi:https://doi.org/10.1109/WSC57314.2022.10015418.

Kenan, N. & Diabat, A. (2022), ‘The supply chain of blood products in the wake of the COVID-19 pandemic: Appointment scheduling and other restrictions’, *Transportation Research Part E: Logistics and Transportation Review* **159**, 102576. doi:https://doi.org/10.1016/j.tre.2021.102576.

Kılıç, H. & Güneş, E. D. (2024), ‘Patient adherence in healthcare operations: A narrative review’, *Socio-economic planning sciences* **91**, 101795. doi:https://doi.org/10.1016/j.seps.2023.101795.

Kim, S.-H., Zheng, F. & Brown, J. (2024), ‘Identifying the bottleneck unit: Impact of congestion spillover in hospital inpatient unit network’, *Management Science* **70**(7), 4200–4218. doi:https://doi.org/10.1287/mnsc.2023.4887.

Knerich, V., Jones, A. A., Seyedin, S., Siu, C., Dinh, L., Mostafavi, S., Barr, A. M., Panenka, W. J., Thornton, A. E., Honer, W. G. et al. (2019), ‘Social and structural factors associated with substance use within the support network of adults living in precarious housing in a socially marginalized neighborhood of Vancouver, Canada’, *PLOS One* **14**(9), e0222611. doi:https://doi.org/10.1371/journal.pone.0222611.

Kuo, R., Song, P., Nguyen, T. P. Q. & Yang, T. (2023), ‘An application of multi-objective simulation optimization to medical resource allocation for the emergency department in taiwan’, *Annals of Operations Research* **326**(1), 199–221. doi:https://doi.org/10.1007/s10479-023-05374-7.

Laidler, G., Nelson, B. L. & and, N. G. P. (2025), ‘Simulation shapelets: Comparing characteristics of time-dynamic trajectories’, *Journal of Simulation* **19**(5), 578–595. doi:https://doi.org/10.1080/17477778.2024.2449033.

Lane, H., Sarkies, M., Martin, J. & Haines, T. (2017), ‘Equity in healthcare resource allocation decision making: A systematic review’, *Social Science & Medicine* **175**, 11–27. doi:https://doi.org/10.1016/j.socscimed.2016.12.012.

Law, A. M. (2022), How to build valid and credible simulation models, *in* ‘2022 Winter Simulation Conference (WSC)’, pp. 1402–1414. doi:https://doi.org/10.1109/WSC40007.2019.9004789.

Leerapan, B., Teekasap, P., Urwannachotima, N., Jaichuen, W., Chiangchaisakulthai, K., Udomaksorn, K., Meeyai, A., Noree, T. & Sawaengdee, K. (2021), ‘System dynamics modelling of health workforce planning to address future challenges of Thailand’s Universal Health Coverage’, *Human resources for health* **19**(1), 31. doi:https://doi.org/10.1186/s12960-021-00572-5.

Macal, C. M. (2016), ‘Everything you need to know about agent-based modelling and simulation’, *Journal of Simulation* **10**(2), 144–156. doi:https://doi.org/10.1057/jos.2016.7.

McKiernan, E. C., Bourne, P. E., Brown, C. T., Buck, S., Kenall, A., Lin, J., McDougall, D., Nosek, B. A., Ram, K., Soderberg, C. K. et al. (2016), ‘How open science helps researchers succeed’, *elife* **5**, e16800. doi:https://doi.org/10.7554/eLife.16800.

Monks, T., Currie, C. S., Onggo, B. S., Robinson, S., Kunc, M. & Taylor, S. J. (2019), ‘Strengthening the reporting of empirical simulation studies: Introducing the STRESS guidelines’, *Journal of Simulation* **13**(1), 55–67. doi:https://doi.org/10.1080/17477778.2018.1442155.

Monks, T. & Harper, A. (2023*a*), ‘Computer model and code sharing practices in healthcare discrete-event simulation: a systematic scoping review’, *Journal of Simulation* **0**(0), 1–16. doi:https://doi.org/10.1080/17477778.2023.2260772.

Monks, T. & Harper, A. (2023*b*), ‘Improving the usability of open health service delivery simulation models using python and web apps’, *NIHR Open Research* **3**, 48. doi:https://doi.org/10.3310/nihropenres.13467.2.

Monks, T., Harper, A. & Mustafee, N. (2024), ‘Towards sharing tools and artefacts for reusable simulations in healthcare’, *Journal of Simulation* **0**(0), 1–20. doi:https://doi.org/10.1080/17477778.2024.2347882.

Morgan, L. E. & Barton, R. R. (2025), ‘Statistical process control for queue length trajectories using fourier analysis’, *European Journal of Operational Research* **325**(2), 233–246. doi:https://doi.org/10.1016/j.ejor.2025.03.013.

Munafò, M. R., Nosek, B. A., Bishop, D. V. M., Button, K. S., Chambers, C. D., Percie du Sert, N., Simonsohn, U., Wagenmakers, E.-J., Ware, J. J. & Ioannidis, J. P. A. (2017), ‘A manifesto for reproducible science’, *Nature Human Behaviour* **1**, 0021. doi:https://doi.org/10.1038/s41562-016-0021.

Mustafee, N., Harper, A., Monks, T. & Shine, R. (2024), ‘Improving urgent and emergency care decisions in the south west’, *Impact* **2024**(1), 14–19. doi:https://doi.org/10.1080/2058802X.2024.2388427.

Nature Biotechnology (2019), ‘Changing coding culture’, *Nature Biotechnology* **37**(5), 485–485. doi:https://doi.org/10.1038/s41587-019-0136-9.

Nelson, B. L. (2016), ‘Some tactical problems in digital simulation’ for the next 10 years’, *Journal of Simulation* **10**(1), 2–11. doi:https://doi.org/10.1057/jos.2015.22.

Ni, Y., Bermudez, M., Kennebeck, S., Liddy-Hicks, S. & Dexheimer, J. (2019), 'Barriers and facilitators to data quality of electronic health records used for clinical research in pediatric emergency care', *BMJ Open* **9**(7), e029314. doi:https://bmjopen.bmj.com/content/9/7/e029314.

Oakley, D., Onggo, B. & Worthington, D. (2020), 'Symbiotic simulation for the operational management of inpatient beds: Model development and validation using delta-method', *Health Care Management Science* **23**, 153–169. doi:https://doi.org/10.1007/s10729-019-09485-1.

Onen-Dumlu, Z., Harper, A. L., Forte, P. G., Powell, A. L., Pitt, M., Vasilakis, C. & Wood, R. M. (2022), 'Optimising the balance of acute and intermediate care capacity for the complex discharge pathway: Computer modelling study during covid-19 recovery in england', *Plos one* **17**(6), e0268837. doi:https://doi.org/10.1371/journal.pone.0268837.

Onggo, B. S., Corlu, C. G., Juan, A. A., Monks, T. & de la Torre, R. (2020), 'Combining symbiotic simulation systems with enterprise data storage systems for real-time decision-making', *Enterprise Information Systems* . doi:https://doi.org/10.1080/17517575.2020.1777587.

Osório, A. (2017), 'Self-interest and equity concerns: A behavioural allocation rule for operational problems', *European Journal of Operational Research* **261**(1), 205–213. doi:https://doi.org/10.1016/j.ejor.2017.01.034.

Palmer, G., Knight, V. A., Harper, P. R. & Hawa, A. L. (2019), 'Ciw: An open-source discrete event simulation library', *Journal of Simulation* **13**(1), 68–82. doi:https://doi.org/10.1080/17477778.2018.1473909,.

Palmer, G. & Tian, Y. (2023), 'Implementing hybrid simulations that integrate DES + SD in Python', *Journal of Simulation* **17**(3), 240–256. doi:https://doi.org/10.1080/17477778.2021.1992312.

Pereira, A. P., Macedo, J., Afonso, A., Laureano, R. M. & de Lima Neto, F. B. (2024), 'The use of social simulation modelling to understand adherence to diabetic retinopathy screening programs', *Scientific Reports* **14**(1), 4963. doi:https://doi.org/10.1038/s41598-024-55517-4.

Perets, O., Stagno, E., Ben Yehuda, E., McNichol, M., Celi, L. A., Rappoport, N. & Dorotic, M. (2025), 'Inherent bias in electronic health records: A scoping review of sources of bias', *ACM Trans. Intell. Syst. Technol.* . doi:https://doi.org/10.1145/3757924.

Pouwels, X. G., Sampson, C. J., Arnold, R. J., Janodia, M. D., Henderson, R., Lamotte, M., Cowell, W., Borrill, J., Huttin, C., Udupa, N., Gong, C. L., Lan, L. S., Brannman, L., Incerti, D., Ramanath, K., Pribil, C., Oleshchuk, O., Pokotylo, O., Schramm, W. & Nuijten, M. (2022), 'Opportunities and barriers to the development and use of open source health economic models: A survey', *Value in Health* **25**(4), 473–479. doi:https://doi.org/10.1016/j.jval.2021.10.001 .

Rachuba, S., Reuter-Oppermann, M. & Thielen, C. (2024), 'Integrated planning in hospitals: a review', *OR Spectrum* pp. 1–54. doi:https://doi.org/10.1007/s00291-024-00797-5.

Rahmandad, H. & Sterman, J. D. (2012), 'Reporting guidelines for simulation-based research in social sciences', *System Dynamics Review* **28**(4), 396–411. doi:https://doi.org/10.1002/sdr.1481 ,.

Rauner, M. & Brandeau, M. (2001), 'AIDS Policy Modeling for the 21st Century: An Overview of Key Issues', *Health Care Management Science* **4**, 165–180. doi:https://doi.org/10.1023/A:1011418614557.

Rhodes-Leader, L. A. & Nelson, B. L. (2023), Tracking and detecting systematic errors in digital twins, *in* '2023 Winter Simulation Conference (WSC)', pp. 492–503. doi:https://doi.org/10.1109/WSC60868.2023.10408052.

Robinson, S. (2014), *Simulation: the practice of model development and use*, Bloomsbury Publishing.

Robinson, S. (2023), 'Exploring the relationship between simulation model accuracy and complexity', *Journal of the Operational Research Society* **74**(9), 1992–2011. https://doi.org/10.1080/01605682.2022.2122740 .

Roby, N., Smith, H., Hurdelbrink, J., Craig, S., Hawthorne, C., DuMontier, S. & Kluesner, N. (2022), 'Characteristics and retention of emergency department patients who left without being seen (LWBS)', *Internal and Emergency Medicine* **17**(2), 551–558. doi:https://doi.org/10.1007/s11739-021-02775-z.

Rodriguez-Cartes, S. A., Mayorga, M. E., Özaltin, O. Y. & Swann, J. L. (2024), Incorporating face mask usage in agent-based models using personal beliefs and perceptions: An application of the health belief model, *in* 'Proceedings of the 2024 Winter Simulation Conference (WSC)', pp. 1071–1082. doi:https://doi.org/10.1109/WSC63780.2024.10838827.

Rutherford, A. R., Zimmerman, S. L., Moeini, M., Barket, R., Ahkioon, S. & Griesdale, D. E. (2022), Simulation model of a multi-hospital critical care network, *in* 'Proceedings of the 2022 Winter Simulation Conference (WSC)', IEEE, pp. 951–960. doi:https://doi.org/10.1109/WSC57314.2022.10015490.

Samota, E. K. & Davey, R. P. (2021), 'Knowledge and attitudes among life scientists toward reproducibility within journal articles: a research survey', *Frontiers in Research Metrics and Analytics* **6**, 678554. doi:https://doi.org/10.3389/frma.2021.678554.

Santric Milicevic, M., Scotter, C., Bruno-Tome, A., Scheerens, C. & Ellington, K. (2024), 'Healthcare workforce equity for health equity: an overview of its importance for the level of primary health care', *The International Journal of Health Planning and Management* **39**(3), 945–955. doi:https://doi.org/10.1002/hpm.3790.

Sapkota, R., Roumeliotis, K. I. & Karkee, M. (2026), 'AI Agents vs. Agentic AI: A Conceptual taxonomy, applications and challenges', *Information Fusion* **126**, 103599. doi:https://doi.org/10.1016/j.inffus.2025.103599.

Schroeck, M. (2020), *Business Prototyping Toolkit for Python (BPTK-Py)*, Transentis Labs. `https://bptk.transentis.com`.

Semwanga, A. R., Nakubulwa, S. & Adam, T. (2016), 'Applying a system dynamics modelling approach to explore policy options for improving neonatal health in uganda', *Health Research Policy and Systems* **14**(1), 35. doi:https://doi.org/10.1186/s12961-016-0101-8.

Smith, H., Currie, C., Chaiwuttisak, P. et al. (2018), 'Patient choice modelling: how do patients choose their hospitals?', *Health Care Management Science* **21**, 259–268. doi:https://doi.org/10.1007/s10729-017-9399-1.

Smith, R., Mohammed, W. & Schneider, P. (2023), 'Packaging cost-effectiveness models in r: A tutorial.', *Wellcome Open Research* **8**(419). doi:https://doi.org/10.12688/wellcomeopenres.19656.1.

Smith, R. & Schneider, P. (2020), 'Making health economic models shiny: A tutorial', *Wellcome Open Research* **5**(69). doi:https://doi.org/10.12688/wellcomeopenres.15807.2.

Smith, R., Schneider, P. & Mohammed, W. (2022), 'Living HTA: Automating Health Economic Evaluation with R', *Wellcome Open Research* **7**, 194. doi:https://doi.org/10.12688/wellcomeopenres.17933.2.

Strategy Unit, T. (2026), 'The New Hospital Programme Demand Model (Version v4.4.0)'.
URL: *https://github.com/The-Strategy-Unit/nhp_model/releases/tag/v4.4.0*

Tako, A. A. & Kotiadis, K. (2015), 'PartiSim: A multi-methodology framework to support facilitated simulation modelling in healthcare', *European Journal of Operational Research* **244**(2), 555–564. doi:https://doi.org/10.1016/j.ejor.2015.01.046.

Taylor, S. J., Anagnostou, A., Fabiyi, A., Currie, C., Monks, T., Barbera, R. & Becker, B. (2017), Open science: Approaches and benefits for modeling & simulation, *in* 'Proceedings of 2017 Winter Simulation Conference (WSC)', IEEE, pp. 535–549. doi:https://doi.org/10.1109/WSC.2017.8247813.

Taylor, S. J., Brailsford, S., Chick, S. E., l'Ecuyer, P., Macal, C. M. & Nelson, B. L. (2013), Modeling and Simulation Grand Challenges: an OR/MS Perspective, *in* 'Proceedings of the 2013 Winter Simulation Conference', IEEE, pp. 1269–1282. doi:https://doi.org/10.1109/WSC.2013.6721514.

Taylor, S. J., Fishwick, P. A., Fujimoto, R., Page, E. H., Uhrmacher, A. M. & Wainer, G. (2012), Panel on grand challenges for modeling and simulation, *in* 'Proceedings of the 2012 Winter Simulation Conference', IEEE, pp. 2614–2628. doi:https://doi.org/10.1109/WSC.2012.6465310.

The King's Fund (2023), Hospital discharge funds: experiences in winter 2022–23, Technical report, The King's Fund. Accessed on 9 February 2026.
URL: *https://assets.kingsfund.org.uk/f/256914/x/ea8416a699/hospital_discharge_funds_2023.pdf*

Tucker, A., Wang, Z., Rotalinti, Y. & Myles, P. (2020), 'Generating high-fidelity synthetic patient data for assessing machine learning healthcare software', *NPJ Digital Medicine* **3**(1), 147. doi:https://doi.org/10.1038/s41746-020-00353-9.

Tuson, M., England, T., Behrens, D., Bowen, R., Edwards, D., Frankish, J. & Kay, J. (2017), 'Modelling for the proposed roll-out of the '111' service in Wales: a case study', *Health Care Management Science* **21**(2), 159–176. doi:http://dx.doi.org/10.1007/s10729-017-9405-7.

van der Ham, R. (2018), Salabim: open source discrete event simulation and animation in python, *in* 'Proceedings of the 2018 Winter Simulation Conference', pp. 4186–4187.

Varney, J., Bean, N. & Mackay, M. (2019), 'The self-regulating nature of occupancy in icus: stochastic homoeostasis', *Health Care Management Science* **22**(4), 615–634. doi:https://doi.org/10.1007/s10729-018-9448-4.

Wang, L. & Demeulemeester, E. (2023), 'Simulation optimization in healthcare resource planning: A literature review', *Iise Transactions* **55**(10), 985–1007. doi:https://doi.org/10.1080/24725854.2022.2147606.

Wojciechowski, J., Hopkins, A. M. & Upton, R. N. (2015), 'Interactive pharmacometric applications using R and the shiny package', *CPT: pharmacometrics & systems pharmacology* **4**(3), 146–159. doi:https://doi.org/10.1002/psp4.21.

World Health Organization (2012), 'Systems and the effect of complexity on patient care', Handout for "To Err Is Human" course. Accessed on September 9 2025.
URL: *https://cdn.who.int/media/docs/default-source/patient-safety/curriculum-guide/resources/ps-curr-handouts/course03_handout_systems-and-the-effect-of-complexity-on-patient-care.pdf*

Wu, J. T., Riley, S. & Leung, G. M. (2007), 'Spatial considerations for the allocation of pre-pandemic influenza vaccination in the united states', *Proceedings of the Royal Society B: Biological Sciences* **274**(1627), 2811–2817. doi:https://doi.org/10.1098/rspb.2007.0893.

Xinying Chen, V. & Hooker, J. N. (2023), 'A guide to formulating fairness in an optimization model', *Annals of Operations Research* **326**(1), 581–619. doi:https://doi.org/10.1007/s10479-023-05264-y.

Xu, J., Huang, E., Hsieh, L., Lee, L. H., Jia, Q.-S. & Chen, C.-H. (2016), 'Simulation optimization in the era of industrial 4.0 and the industrial internet', *Journal of Simulation* **10**(4), 310–320. doi:https://doi.org/10.1057/s41273-016-0037-6.

Xu, X., Li, L. & Wu, H. (2008), Cooperation policy simulation in urban health care system, *in* '2008 IEEE International Conference on Service Operations and Logistics, and Informatics', Vol. 1, IEEE, pp. 447–451. doi:https://doi.org/10.1109/SOLI.2008.4686437.

Yin, X., Büyüktahtakın, İ. E. & Patel, B. P. (2023), 'COVID-19: Data-driven optimal allocation of ventilator supply under uncertainty and risk', *European Journal of Operational Research* **304**(1), 255–275. doi:https://doi.org/10.1016/j.ejor.2021.11.052.

Yuan, Y., Gafni, A., Russell, J. D. & Ludwin, D. (1994), 'Development of a central matching system for the allocation of cadaveric kidneys: A simulation of clinical effectiveness versus equity', *Medical Decision Making* **14**(2), 124–136. doi:https://doi.org/10.1177/0272989X9401400205.

Zenios, S. A., Chertow, G. M. & Wein, L. M. (2000), 'Dynamic allocation of kidneys to candidates on the transplant waiting list', *Operations Research* **48**(4), 549–569. doi:https://doi.org/10.1287/opre.48.4.549.12418.

Zečević, K., Houghton, C., Noone, C., Lee, H., Matvienko-Sikar, K. & Toomey, E. (2021), 'Exploring factors that influence the practice of open science by early career health researchers: a mixed methods study', *HRB Open Res* **3**, 56. doi:https://doi.org/10.12688/hrbopenres.13119.2.

Zhang, X., Lhachimi, S. K. & Rogowski, W. H. (2020), 'Reporting quality of discrete event simulations in healthcare—results from a generic reporting checklist', *Value in Health* **23**(4), 506–514. doi:https://doi.org/10.1016/j.jval.2020.01.005.

Zimmerman, S., Rutherford, A., van der Waall, A., Norena, M. & P, D. (2023), 'A queuing model for ventilator capacity management during the covid-19 pandemic', *Health Care Management Science* **26**(2), 200–216. doi:https://doi.org/10.1007/s10729-023-09632-9.