

EXPLORING REUSABILITY BARRIERS FOR SIMULATION MODELS IN HEALTHCARE

Lucy Morgan^{1,2}, Alison Harper³, Thomas Monks⁴, Amy Heather⁴, and Steffen Zschaler⁵

¹The Strategy Unit, NHS, UK

²The Department of Management Science, Lancaster University, Lancaster, UK

³Centre for Simulation, Analytics, and Modelling, University of Exeter Business School, Exeter, UK

⁴The Medical School, University of Exeter, Exeter, UK

⁵Department of Informatics, King's College London, UK

ABSTRACT

Simulation models offer significant potential for improvements to healthcare operations. However, a lack of reuse of existing models makes it difficult to realize this potential. The practical barriers to model reuse in healthcare remain poorly understood. We report findings from a qualitative study exploring reusability barriers for open, published simulation models within National Health Service settings. We conducted semi-structured interviews with seven healthcare data analysts and applied thematic analysis to identify key barriers and facilitators. This revealed nine themes: time and resource constraints, skill-related barriers, documentation quality, model interfaces and outputs, stakeholder engagement and trust, governance and data management, calibration and validation challenges, model discoverability, and model adaptability and extensibility. We discuss implications for simulation researchers and model developers, arguing technical reproducibility alone is insufficient for meaningful reuse. Instead, reuse requires deliberate attention to organizational context, model purpose, user capability, and design for reuse, alongside open-source practices.

1 INTRODUCTION

Healthcare simulation has a long track record of technical capability, yet repeated reviews and empirical accounts note that simulation is not routinely embedded in National Health Service (NHS) decision-making. Even where models are technically credible, the pathway from a 'published model' to a 'used tool' remains weak, with studies reporting analytic potential rather than sustained operational use. Foundational work on simulation reuse suggests that while reuse promises economic and quality benefits, it is constrained by issues of validity, credibility, and adaptation cost (Robinson et al. 2004). More recent systems-design literature has formalized methods and levels of reuse and the preparatory steps required to enable discovery, interpretation, and composability (Hussain et al. 2022; Zschaler et al. 2025).

In healthcare simulation specifically, Monks et al. (2024) proposes a framework for supporting reuse in healthcare contexts, while Heather et al. (2025) emphasizes technical reproducibility through the sharing and structuring of model code and related artifacts. These approaches provide important guidance on how reuse and reproducibility can be supported. However, their adoption does not necessarily mean that published models are reused, or that they are considered usable and trustworthy by independent healthcare organizations in practice. Developing an empirical understanding of the barriers faced by such users is essential to assess whether these approaches are sufficient to enable meaningful cross-organizational transfer.

More broadly, constraints related to data governance, model complexity, and stakeholder-specific knowledge and motivation continue to pose significant challenges for both reuse and reproducibility (Uhrmacher et al. 2016; Goyal et al. 2026; Crowe et al. 2024). England et al. (2025) argued that attention should shift from technical reproducibility toward the conditions under which externally developed models can be understood, adapted, and meaningfully applied by new organizational users. Despite growing attention to reproducibility and reusable architectures, there remains limited empirical evidence on whether published, open simulation models can be independently reused within NHS settings. In particular, little is

known about the organizational, conceptual, and technical challenges that arise when a model is transferred across settings without direct developer involvement.

This paper begins to address that gap by exploring the practical, cross-organizational reusability of an open, discrete-event simulation (DES) model with NHS users, focusing on usability, conceptual alignment, data translation, credibility, and perceived usefulness. Through a multi-site study, this paper aims to:

1. Identify organizational, conceptual, and technical barriers to model reuse in the NHS
2. Derive implications for the design, reporting, and dissemination of reusable healthcare simulation models, and a research agenda for practical reuse.

2 RELATED WORK

Generic or reusable models are often presented as a solution to repeated bespoke development, particularly in health systems such as the UK NHS, where organizations are similarly structured and face comparable operational challenges. Fletcher and Worthington (2009) described a spectrum ranging from highly abstract generic principles, through setting-specific generic models, to fully bespoke local models. Along this spectrum, the design intent influences documentation and parameterization requirements, and implementation pathways. The authors explored how models could be reused in practice and highlighted that successful transfer depends on explicit separation of structural assumptions from local data, careful parameterization, and clear articulation of modelling intent. Their findings suggest that while reuse is feasible, it requires deliberate design and adaptation rather than simple replication across settings.

At a broader level, simulation reuse has been conceptualized as requiring supporting infrastructure. Zschaler et al. (2025) synthesized reuse strategies into a triadic framework encompassing open-science reuse, gray-box reuse through modeling languages, and black-box reuse of model components. Parallel efforts in the simulation community have focused on improving reproducibility through enhanced documentation and code sharing. However, Uhrmacher et al. (2016) observed that many published simulation studies lack sufficient information to enable reuse, a concern reported more recently by Monks and Harper (2023).

Where reuse has been attempted, organizational and contextual barriers have been documented. Conceptual mismatch between model structure and local processes, variability in data availability and quality, and differences in motivation and analytical capacity can hinder reuse (Crowe et al. 2024). England et al. (2025) reframed this as a problem of practical reusability, arguing that independently developed models must be interpretable, adaptable, and contextually meaningful to new organizational users. They emphasized that clinicians and managers may place greater trust in models they were involved in developing, while externally developed or highly generic “one-size-fits-all” models can trigger skepticism regarding applicability and local fit. Similarly, in Uhrmacher et al. (2016), Brailsford observed the persistence of “not invented here” syndrome, where stakeholders resist externally developed models, even when structural similarities exist. This perceived lack of conceptual alignment, and the blackbox nature of simulation models, can undermine trust and limit reuse, irrespective of methodological credibility (Harper, Mustafee, and Yearworth 2021).

Empirical studies of healthcare simulation adoption reinforce these concerns. Qualitative evaluation of a commercial off-the-shelf tool identified barriers extending beyond software access, including limited time and capacity, variable analytical skill base, data challenges, and perceived misalignment with local work practices (Brailsford et al. 2013). A healthcare user-driven development study similarly emphasized that practical uptake depends on usability, versatility, meaningful outputs, and ongoing support structures, particularly where models are transferred from academic development to NHS use (Tyler, Murch, Vasilakis, and Wood 2022). Notably, Crowe et al. (2024) demonstrated that even when reuse is explicitly supported through structured collaboration and sustained researcher involvement, organizational readiness, data constraints, and competing priorities can impede transfer. This raises the question whether independently published open models can be reused under more typical NHS conditions, where embedded support is absent.

Similar adoption challenges have been documented beyond healthcare. In manufacturing, survey-based research and expert opinion have identified data integration barriers, limited internal expertise, tool

interoperability gaps, and organizational readiness constraints as persistent impediments to effective DES use (Goyal, Yamamoto, and Aslanidou 2026; Knoll and Heim 2000). These studies evaluated general adoption and uptake, but did not examine the specific challenges associated with independently reusing externally developed models across organizational settings. The literature highlights a persistent gap between reproducible, credible simulation research and practical cross-organizational reuse, motivating the need to understand how models can be transferred, interpreted, and trusted within new organizational contexts.

3 METHODOLOGY

In this section we discuss how participants were recruited to the study, barriers to recruitment, the open simulation model used in the study, and study components. There were two components: the first required participants to attempt to reuse an open model by following a provided list of steps; and the second was an interview where we asked participants about their experience of attempting to reuse the model.

3.1 Participant Recruitment

Participants were recruited via two routes: by direct approach to NHS contacts, and through open calls to join the study posted on social media platforms such as LinkedIn, the NHS-Open Analytics (NHS-OA) Slack, or via mailing lists like the Health and Care Operational Research Network (HaCORN).

After registering initial interest in joining, the study participants received an information sheet outlining the task and time commitments. If happy to proceed, they were then asked to email the study lead to confirm their place. Interest in joining the study was high with 17 initial responses of interest of which 7 chose to be involved. Of those that were interested but did not take part, some stated that they could not get the required permissions to be involved, some were concerned about the time commitment and others mentioned problems around lack of data access. Those that entered into the study then received a participant instruction sheet outlining the study protocol, see Section 3.3. All participant materials are available from [FigShare](#) (Morgan, Harper, Monks, Heather, and Zschaler 2026).

All seven participants were healthcare data analysts working within the NHS with a range of experience levels and years working in healthcare. All participants had some familiarity with coding in R or Python and used at least one of these within their daily roles. Multiple participants noted that they were the sole data scientist or R/Python programmer within their organization, while others were part of a wider analytics team. Experience in using open-source repositories was mixed with some participants having used or developed their own code repositories and others being beginners. Participants had limited experience of working with or constructing simulation models, but they were all familiar with simulation and wanted to learn more. There was also an enthusiasm across the group for model reuse, with calls for a community to be developed to support this growing area.

3.2 Model Summary

During the study, participants were instructed to work with an open simulation model for stroke capacity planning. This choice was based on the availability of suitable open simulation models, and what we believed would be a system with widely shared understanding across participants.

The stroke capacity planning model (Figure 1) is a DES model representing patient flow from first presentation with suspected stroke through acute inpatient care, rehabilitation, and discharge, originally developed in SIMUL8 (Monks et al. 2016). The model reports service performance measures such as bed occupancy, admissions, delays, and throughput for acute and rehabilitation units.

This study uses two reimplementations of the model (Heather and Monks 2026a; Heather and Monks 2026b), as described in (Heather et al. 2026). They are developed in Python using SimPy (Team SimPy 2024) and in R using simmer (Ucar et al. 2019). In both languages, the core simulation is structured as a package, with downstream analyses carried out in notebooks (Python) or R Markdown documents (R). Dependencies are managed using conda (Python) and renv (R), and both codebases are released under an

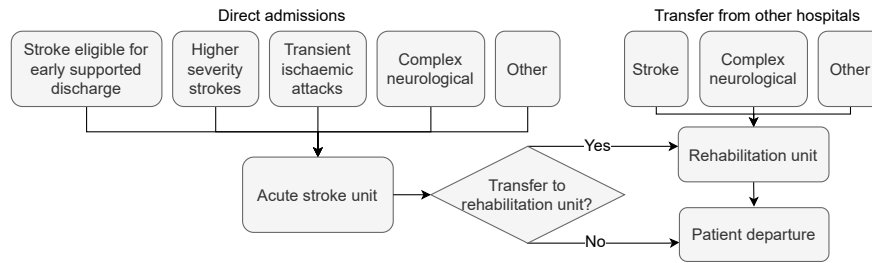


Figure 1: Model structure.

MIT license. Each repository includes a README describing how to install and run the model, reproduce the figures and tables from the paper, and execute automated verification tests.

3.3 Study Protocol

Participants were asked to follow a set of steps (reproduce, realign and then reuse an open model) provided in the instruction sheet, and to think about the accompanying questions. Due to the time restriction, some tasks were marked as optional, but were included for completeness. We asked participants to spend up to 4 hours with the model, with any additional time at their own discretion. There was no requirement to complete all steps in one sitting, so we asked participants to keep an activity log as they worked through the study steps to avoid issues, however small, being forgotten.

Participants were asked to complete each step of the protocol in turn. At each stage we asked them to stop when they reached a point at which they could not proceed any further, and then progress on to the next step. We made clear that partial progress was also valuable to the study and that we were looking for feedback on the model and its documentation, not their performance.

3.4 Participant Interview Design

We conducted semi-structured interviews, following a structured multistep template (see dataset), informed by findings from previous studies (Brailsford et al. 2013; England et al. 2025; Tyler et al. 2022), including follow-up exploratory prompts. Each interview lasted approximately 45 minutes.

3.5 Qualitative Data Analysis

Interview transcripts were automatically transcribed, manually cleaned of off-topic content and errors, and subjected to LLM-assisted inductive thematic analysis (ITA). Analysis used a locally hosted open-weight LLM (OpenAI’s gpt-oss:120b; temperature=0.3; max context=32,768 tokens) on an NVIDIA H100 GPU, via Python 3.12, langchain-ollama v1.0.1, and Ollama v0.20.0. We followed a two-round protocol from the HACITA framework (Nyaaba et al. 2025), where the LLM scaffolds the workflow while the research team retains interpretive authority.

In round one, transcripts were split into chunks (4,000 characters, 10% overlap) and analyzed independently. The LLM iteratively processed chunks and existing codebook. We used a variation of Tree of Thoughts (Yao et al. 2023): the LLM simulated four "expert" problem solvers (focused on reuse barriers, facilitators, required changes, outliers) plus a consolidator to merge/reduce codes. Finally, we passed all codebooks to the LLM and prompted it to produce a single codebook of unified study-level themes.

In the second round, each transcript was reanalyzed independently against the consolidated theme list, with the model prompted to confirm which themes were evidenced in the transcript, and flag any emergent themes not yet captured. Analyzing transcripts individually, rather than in a single combined pass, mitigates the risk that low-frequency but important barriers, potentially arising in only one or two interviews, are suppressed in favor of the most commonly occurring themes (Khalid and Witmer 2025). This per-transcript

structure also aligns with traditional ITA practice, with initial coding at the level of individual data sources before cross-dataset synthesis (Nyaaba et al. 2025; Bakharia et al. 2025). Subsequently, identified themes were used as a scaffold to consolidate and finalize themes and evidence cross-checks.

The consolidated codebook and associated themes were reviewed collaboratively, with the research team discussing the themes identified by the model and comparing them against their own interpretations of the interviews. Additionally, individual interview codebooks and candidate quotes were revisited to confirm that the final thematic structure faithfully represented those codes and quotes. Key illustrative quotes for the themes selected for reporting were then identified and cross-checked against the original recordings to ensure that each quotation was accurately transcribed and appropriately grounded in participants' accounts.

4 FINDINGS

Time and Resource Barriers. Within the study, participants were asked to spend no more than half a day completing the protocol tasks, so it is not surprising that time was identified as a barrier to reusing. For example, the time needed to access data clearly prevented some participants from completing later stages of the protocol:

“If I was attempting to use this because I had a genuine situation to apply it to, there would have been an awful lot more thought up front to have got the data in to do it [...] no way that was going to happen because it would have taken weeks of work to get” (Participant 1)

Time constraints also emerged as a more general recurring theme throughout. Some analysts described the strain on their own time under competing analytical duties being a barrier to model reuse:

“it is a relatively chaotic environment to work with in a trust and you kind of rarely get these big blocks of time to really get into reading anything” (Participant 2)

Others noted that challenges in securing the time of clinical staff to engage with a model impacts the ability to make impact. However, one participant suggested that writing models from scratch would lead to lower output and saw reuse (of open source analytical products) as a key part of their role:

“if I can use models that have been developed in other places and make them appropriate for our data, then that’s going to be much more beneficial to our hospital in terms of the amount of data science that we can provide. So reusability is really part of my job.” (Participant 3)

Not all participants saw resource as a barrier however, with some highlighting the benefit of open source code negating the need for costly licenses. There was acknowledgment within the group however that the step towards free model development requires an (often steep) learning curve and thus time for skill development. Another consideration is the psychological barrier in switching away from commercial software as the default for simulation model development.

Skill-Related Barriers. The model made assumptions about the skill level of the users, for example, their understanding of DES and their proficiency with Python/R and GitHub. These assumptions were not valid for all study participants, creating barriers to reuse.

“In the participant instruction sheet, [...] I would expect more information on the basics of discrete event simulation, that would be really helpful for us” (Participant 4)

“I found that the instructions assumed some knowledge that I didn’t have. [...] In hindsight, it’s really obvious where to run those, but at the time, I’m sitting there thinking, okay, do I run this in Git Bash? Do I run this in RStudio?” (Participant 3)

Models can be difficult to reuse because of the need to set up the correct execution environment first, which can be a barrier for users who are not proficient with programming or with the specific tools used to develop the model. For example:

“everything is always wrong, no matter what you’re doing, every time you start a new project, you’ve always got to find some working environment.” (Participant 1)

“If I hadn’t encountered `renv` before, I think that would have maybe been a bit of a stopper” (Participant 2)

Participants highlighted that familiarity with tools and conventions are important requisites for effective reuse. While documentation can support this, unfamiliar formats or infrastructure still made repositories harder to navigate and adapt. For example, the use of JSON files for parameters was straightforward for some but created challenges for others.

However, skills barriers go beyond the technical reproducibility of the model, and include understanding the underlying assumptions and methodology. For example:

“I’m not fully confident about the underlying statistical methodology like Erlang loss formula and how occupancy distributions are used to calculate the probability of delay” (Participant 4)

“Why do we use a log normal distribution for a hospitalization? Because there is a, it’s a left skewed, is it?” (Participant 6)

These barriers often depend on who is trying to reuse the model:

“I had to go in and see what each file had in them and kind of read the object classes. I think maybe that would be quite hard for someone who doesn’t really know that that’s there” (Participant 5)

“If at the same time I wanted to ask that same analyst who uses Excel predominantly to change something more to the model, not just the parameters, then I think they would hit a bit of a brick wall” (Participant 6)

One participant suggested there is a wider skills gap in the NHS around open-source tools, which creates a barrier to reuse:

“we’ve not got a consistent set of skills, particularly in using open source stuff” (Participant 1)

Skill barriers are not purely an objective issue, but also relate to the confidence of users in their own skills and the perceived complexity of the task:

“I’m not confident enough to build this model from scratch. [...] To replicate it [...] I can do it in like six months. If I do it from scratch maybe it would take me like two years.” (Participant 4)

Documentation Barriers. Within the participant instruction sheet we suggested that participants read the paper upon which the model repository was based, then attempt to reproduce and reuse the model. We therefore include the paper as a form of model documentation. The paper introduces the methodology and assumptions behind the model, and includes a conceptual diagram of the stroke pathway. Within the

repository the README.md provided a link to the paper, a model diagram and instructions for use and reproducing results from the article.

Information about the model being provided in two separate documents divided the participants. Some participants commented on not having enough time to read the paper thoroughly, or finding it hard to connect the paper content to the repository output.

“it took me a while to figure out what the outputs in the paper actually were and what the graphs in the paper actually were.” (Participant 7)

Whereas some argued that the paper provided necessary context to understand the model

“I guess you can just read the repo and kind of get an idea of what it does, but the purpose of it is really more thoroughly explained in the paper.” (Participant 5)

Despite the paper being a detailed presentation of methodology, it was not written with reproducibility in mind. More than one participant noted that some of the modelling decisions were not clearly presented, including information about patient cohorts and diagnosis codes which meant they had to make localized assumptions about these when working with their own data. This is a symptom of the repository having been built after the paper was written. One highlighted benefit of clear concise documentation is the sustainability it creates when staff turnover is high:

“If you can put all the documentation there and make it as easy for people to reuse as possible, then hopefully if the person behind it did move on, then that wouldn’t be too sort of stymieing for it still being useful in the future.” (Participant 3)

However, in general there seemed to be disagreement about how much information to include, and whether a repository should be able to stand alone without the need for reading the paper. One participant suggested that a short summary of the key paper findings would have helped signpost the repository more effectively, while another noted that the function of the README file is to be clear, concise and specific, and not all the information in the paper would be relevant to include for all users:

“So having a README, which is super clear, super analytical, but it’s also, I don’t know, 15 pages, who’s going to read it? I don’t think that many people will.” (Participant 6)

It is clear that the documentation needs of the user differ depending on how they are trying to use the model and their knowledge base. It was also raised that a standardized way to document a repository for a reusable model would provide consistent expectations of what is/is not included.

Model Interfaces and Outputs. A key consideration for participants was the need to match model interfaces to the intended users:

“[...] do you want the model to be analyst driven or do you want the model to be stakeholder driven? [...] one thing you could do with this model is to kind of like put a GUI around it and kind of let the stakeholders adjust the parameters themselves [...] or whether [...] the analyst can drill into the data and probably kind of simplify the kind of understanding of the model and present the results” (Participant 7)

“And this is where I think web stuff is quite useful as well [...] You know, they’re the thing that you say, you send to the service manager and say, look, there you go, there’s the output.” (Participant 1)

Different model interfaces also impact how easily a model can be adapted to a new context:

“If you were doing that [using an AnyLogic model], it’s almost you could drag in a box and just make a few configuration changes. Whereas here, I think I’m not sure how much you’d fundamentally have to change the architecture of the code, you know, almost like rip it up and start again.” (Participant 7)

Visualizations are deemed to be key for model understanding, and, thus, for successful reuse, but need to be carefully designed and provided with sufficient context to be easily interpretable by users.

“for the purpose of me trying to understand the model and what it’s doing, it would be really nice to have some like visual outputs showing what the model’s doing over time. [...] something just like, you know, one chart for the ASU beds and one chart for the rehab beds, that sort of thing.” (Participant 3)

Stakeholder Engagement and Trust. Stakeholder engagement emerged as one of the most practically challenging aspects of model reuse, and one that is easily underestimated by analysts focused on the technical task. Participants described the difficulty of securing time with clinicians:

“[...] an issue was actually trying to get time with the stakeholders, because I basically had to corner them [...] please sit down with me 10 minutes to do this, because with emails I didn’t get very far.” (Participant 5)

Conventional model workflow, where an operational problem drives the analysis, was effectively inverted, which made engagement difficult, as participants were starting with a potential solution.

“It’s less likely that I would say, oh, here’s a model for stroke and approach our stroke service. It’s more likely that I will bear this in mind until a question crops up that comes the way of our business intelligence unit.” (Participant 3)

However, engagement was considered non-optional, as meaningful validation requires clinical and management input that analysts alone cannot provide.

“A lot of the validation of the model needs to be done with stakeholders [...] they say, no, there are guidelines that say a patient can only wait eight days; or that would never happen in reality” (Participant 5)

Trust in the model and its underlying methods was a second, closely-related theme. Analysts described a personal threshold of confidence that needed to be met before they would consider reusing a model. For some, trust was conferred via academic provenance, for others by visible reuse, viewed as endorsement, across multiple other NHS settings, and for many, by their own confidence in using the model.

Governance, Security, and Data. Participants identified data access and consistency as significant barriers to reuse. Several analysts lacked access to the data required to parametrize the model for their local context, whether due to working at a regional level removed from organizational-level records, or because relevant data simply was not collected.

Even where data existed, cross-organizational inconsistency undermined transferability:

“You can’t be confident that one organization to the next are generating the data in the same way [...] we’re such a kind of mixed economy of different systems” (Participant 1)

In some cases, IT governance and security policies created further, often insurmountable, practical barriers. Analysts described hesitancy around installing external code, particularly where it had not been externally verified by other NHS organizations, while locked NHS computers meant that installing dependencies required IT support tickets, and in some Trusts Python, R, and Git were prohibited. Resolving

these issues frequently required senior buy-in, adding a challenging organizational and political dimension to what might otherwise appear a purely technical problem.

Calibration and Validation. Participants approached validation by applying informal face validity checks. Varying inputs such as arrival rates and observing whether outputs responded as expected, rather than formal calibration procedures, with Participant 2 describing this as “*the very minimum amount of checking*” needed. One participant noted a technical barrier in terms of input modelling and the statistical distributions embedded in the model. NHS length-of-stay data frequently exhibits heavy long tails that cannot be well represented with standard parametric distributions.

“Some of the distributions in the NHS [...] follow this weird long tail [...] we often try and sample from historic patients rather than fitting to a distribution” (Participant 7)

Discoverability of Models. One participant noted that, while there is interest in reusing existing models, it is not always clear where to find work developed within the NHS, as noted by Participant 2, “*how do you actually find out that someone has developed a lovely model[...]?*”

“My dream scenario is, yeah, is that most trusts have GitHubs, and we have like a central, you know, repository [...] Most trusts have roughly the same issues, and we have a lot of people wasting time [...] they start from scratch, whereas if they said, oh, let me just go to the NHS GitHub and [...] People have solved this in this way and that way.” (Participant 5)

They argued that publicly funded analytical work should be easier to find and reuse:

“We are public servants. So why, if people are paying us to contribute to the NHS, why [not share solutions. . .] even someone outside the NHS should be able [to] see how people in the NHS solve this problem, you know, and . . . even contribute to it. You know, we’re civil servants, so why are we keeping things under lock and key?” (Participant 5)

Model Adaptation, Extendability and Flexibility. Participants broadly distinguished between two levels of model reuse: changing parameters, which was seen as accessible, and structural extension, e.g., adding patient categories, new wards, or decision logic, which was not. Even technically confident participants were uncertain where in the codebase to make such changes.

“Once you found where the model parameters are, then it’s easy to change the parameters... fast and kind of easy.” (Participant 2)

Beyond skills, participants noted that specific model assumptions, First-In-First-Out queuing, fixed ward overflow behavior, would need reworking for their context, and that the outputs a re-user needs depend entirely on the question being asked, which varies across reuse settings.

5 DISCUSSION

The findings of this study come from a different perspective (the NHS analyst) than previous model re-use research where the model reuse was predominantly driven and supported by the original model developer (England et al. 2025; Crowe et al. 2024). We instead allowed participants to approach the open-source model with minimal intervention to mimic the situation where an analyst would actively look for an open-source tool to solve a problem rather than build something from scratch.

As perhaps would be expected, some of the themes found here (documentation, competing priorities, organizational readiness, data constraints and skills barriers) were also reported in previous studies (Brailsford et al. 2013; Tyler et al. 2022; Crowe et al. 2024). That these barriers continue to exist, despite advances in open source tooling, structured reporting standards, and reproducibility guidance (Monks et al. 2024;

Heather et al. 2025; Monks et al. 2019) reinforces the findings by England et al. (2025) that the field must pay attention to practical, as well as technical, reuse.

Several findings extend the existing literature. First, the absence of ‘not invented here’ syndrome, prominently reported by Brailsford et al. (2013), was notable. In part, we attribute this to the data science background of participants, where code sharing and code re-use is much more common place than for those from a modeling or operational research background. For the participants, trust in the model was somewhat implicit because the model came from a peer-reviewed academic source and prior NHS use.

Participants consistently distinguished between analyst-driven reuse, requiring programming proficiency, and stakeholder-driven reuse, which requires only interpretable outputs and an accessible interface. Several noted that a web-based front-end would substantially lower barriers to validation, by enabling clinicians to interrogate model behavior, and dissemination, by allowing outputs to be shared with service managers directly. Analyst-driven reuse, which may require code adaptation, added an empirical dimension to the spectrum described by Fletcher and Worthington (2009) and the challenges identified by Zschaler et al. (2025). Stakeholder-driven reuse is partly addressed by Monks et al. (2024), and the practical importance emphasized for independent reuse.

Open-source models offer a clear cost advantage over commercial alternatives, but the value goes further than cost, as NHS trusts face broadly similar operational problems. A single well-designed reusable model could benefit many organizations, making the return on investment far greater than any individual trust’s development effort. Participants understood this, describing reusability as central to their role, and were keen to build a shared NHS modelling community. The findings suggest that the primary barrier is not motivation, but the organizational conditions – protected time, reliable infrastructure access, and sustained investment in analytical capability – needed to act on it.

A theme with no clear precedent in the simulation reuse literature was the discoverability of open models. Participants described being unaware of relevant existing models. Currently, only a few NHS trust-based analytical teams are using open-source approaches due to disparities in digital maturity (Bennion et al. 2025). Monks and Harper (2023) found that only 8.3% of healthcare DES studies shared model code at all, and among those, a third explained how to run their model and half provided an open license. Existing initiatives, including [HSMA Atlas](#) (HSMA Atlas 2026) and the [NHS Wales Solutions Exchange](#) (NHS Wales 2026) address this gap to some degree, but awareness among NHS analysts appears limited. Parallel work in agent-based modeling has addressed this through structured repositories such as CoMSES-Net, which enforces metadata standards and supports discovery and citation. A comparable infrastructure, integrated within existing NHS analytical communities and social platforms may be a more tractable near-term solution than a single centralized repository.

From the participants’ perspective, despite reporting multiple barriers, there was a shared belief that model reuse is both feasible and valuable. To structure these findings, we group the themes into four categories, which provide a conceptual framework for understanding and addressing barriers to simulation reuse in healthcare: *preconditions of reuse* (time, skills, governance); *interaction barriers* (documentation, interfaces); *system-level barriers* (trust, stakeholders, discoverability); and *adaption barriers* (calibration, extensibility). The findings of the study point to several priorities for future research:

Preconditions of reuse highlight the need for research into the organizational conditions required to support sustained reuse. This includes protected analytical time, development of simulation capability within NHS teams, and the impact of governance constraints on the adoption of open-source tools.

Interaction barriers point to the importance of improving how users engage with models. Future work could explore tiered documentation standards tailored to different user groups (Aros 2025), as well as accessible deployment approaches building on existing work (Monks et al. 2024), such as web-based interfaces, that enable both technical and non-technical users to interact with models.

System-level barriers suggest that reuse is not solely a technical problem, but a social and organizational one. Research is needed to understand how trust in externally developed models is established, how

stakeholder engagement can be facilitated when models are introduced without prior co-development, and how discoverability of existing models can be improved through shared repositories or community infrastructure.

Adaptation barriers emphasize the need to design models for structural reuse rather than reproducibility alone. This includes research into modular software architectures, configurable pathways, and flexible input modeling approaches. Future work should explicitly address gray-box reuse (e.g. using domain-specific modelling tools (Godfrey et al. 2023)), enabling more complex model adaptations without requiring full coding skills.

We acknowledge that the participants that engaged with the study were a small sample of individuals that were motivated enough to give their time to join the study and thus had some existing interest in simulation and model reuse. Their views and their skills base may not be reflective of all NHS analysts.

ACKNOWLEDGEMENTS

This work was supported by the Medical Research Council under grant number [MR/Z503915/1]. We thank all interview participants for generously sharing their time and experiences.

REFERENCES

- Aros, S. K. 2025. "Content Considerations for Simulation Conceptual Model Documentation". In *2025 Winter Simulation Conference (WSC)*, 2193–2203: IEEE <https://doi.org/10.1109/wsc68292.2025.11339106>.
- Bakharia, A., A. Shibani, L.-A. Lim, T. McCluskey, and S. B. Shum. 2025. "From Transcripts to Themes: A Trustworthy Workflow for Qualitative Analysis Using Large Language Models".
- Bennion, M and Spencer, R and Moore, R and Kenyon, R 2025. "Digital Capability, Open-Source Use, and Interoperability Standards Within the National Health Service in England: Survey of Health Care Trusts" <https://doi.org/10.2196/66398>.
- Brailsford, S., T. Bolt, G. Bucci, T. Chausset, N. Connell, P. Harper, et al. 2013. "Overcoming the Barriers: A Qualitative Study of Simulation Adoption in the NHS". *The Journal of the Operational Research Society* 64(2):157–168.
- Crowe, S., L. Grieco, T. Monks, B. Keogh, M. Penn, M. Clancy, et al. 2024. "Here's Something we Prepared Earlier: Development, Use and Reuse of a Configurable, Inter-disciplinary Approach for Tackling Overcrowding in NHS Hospitals". *Journal of the Operational Research Society* 75(4):689–704.
- England, T., S. Brailsford, C. Burton, G. Martin, S. M. Mason, L. Maynou, et al. 2025, March. "A New Approach to Getting Simulation Models Used in Healthcare: An Example from Emergency Care". *Journal of the Operational Research Society* 76(12):2579–2590 <https://doi.org/10.1080/01605682.2025.2483787>.
- Fletcher, A., and D. Worthington. 2009. "What is a 'Generic' Hospital Model?—A Comparison of 'Generic' and 'Specific' Hospital Models of Emergency Patient Flows". *Health Care Management Science* 12(4):374–391.
- Godfrey, T., S. Zschaler, R. Batra, S. Douthwaite, J. Edgeworth, M. Edwards et al. 2023. "Supporting Emergency Department Risk Mitigation with a Modular and Reusable Agent-Based Simulation Infrastructure". In *2023 Winter Simulation Conference*, 162–173: IEEE <https://doi.org/10.1109/wsc60868.2023.10407894>.
- Goyal, A., Y. Yamamoto, and I. Aslanidou. 2026. "Adoption of Discrete Event Simulation in Manufacturing". *Journal of Simulation*:1–25 <https://doi.org/10.1080/17477778.2026.2628033>.
- Harper, A., N. Mustafee, and M. Yearworth. 2021. "Facets of Trust in Simulation Studies". *European Journal of Operational Research* 289(1):197–213.
- Heather, A. and Monks, T. 2026a. "Stroke Capacity Planning Model: Python DES RAP" <https://doi.org/10.5281/zenodo.18608967>.
- Heather, A. and Monks, T. 2026b. "Stroke Capacity Planning Model: R DES RAP" <https://doi.org/10.5281/zenodo.18609825>.
- Heather, A., T. Monks, A. Harper, F. Alidoost, R. Challen, T. Slater et al. 2026. "Reproducible analytical pipelines for healthcare discrete?event simulation: An open guide and worked examples [version 1; peer review: awaiting peer review]". *NIHR Open Research* 6(68) <https://doi.org/10.3310/nihropenres.14296.1>.
- Heather, A., T. Monks, A. Harper, N. Mustafee, and A. Mayne. 2025. "On the Reproducibility of Discrete-Event Simulation Studies in Health Research: An Empirical Study Using Open Models". *Journal of Simulation*:1–25.
- HSMA Atlas 2026. "Healthcare Services Analytics & Decision Science Atlas" <https://doi.org/https://atlas.hsma.co.uk/>.
- Hussain, M., N. Masoudi, G. Mocko, and C. Paredis. 2022. "Approaches for Simulation Model Reuse in Systems Design—A Review". *SAE International Journal of Advances and Current Practices in Mobility* 4(2022-01-0355):1457–1471.
- Khalid, M. T., and A.-P. Witmer. 2025. "Prompt Engineering for Large Language Model-assisted Inductive Thematic Analysis". *Social Science Computer Review*:08944393251388098.

- Knoll, J. M., and J. A. Heim. 2000. "Ensuring the Successful Adoption of Discrete Event Simulation in a Manufacturing Environment". In *Proceedings of the 32nd conference on Winter simulation*, 1297–1304.
- Monks, T., C. S. Currie, B. S. Onggo, S. Robinson, M. Kunc, and S. J. Taylor. 2019. "Strengthening the Reporting of Empirical Simulation Studies: Introducing the STRESS Guidelines". *Journal of Simulation* 13(1):55–67.
- Monks, T., and A. Harper. 2023. "Computer Model and Code Sharing Practices in Healthcare Discrete-Event Simulation: A Systematic Scoping Review". *Journal of Simulation* 19(1):108–123 <https://doi.org/https://doi.org/10.1080/17477778.2023.2260772>.
- Monks, T., A. Harper, and N. Mustafee. 2024. "Towards Sharing Tools and Artefacts for Reusable Simulations in Healthcare". *Journal of Simulation* 19(6):619–638.
- Monks, T., D. Worthington, M. Allen, M. Pitt, K. Stein, and M. A. James. 2016. "A Modelling Tool for Capacity Planning in Acute and Community Stroke Services". *BMC Health Services Research* 16(1):530.
- Morgan, L. and Harper, A. and Monks, T. and Heather, A. and Zschaler, S. 2026. "Data and study materials for paper "Exploring Reusability Barriers for Simulation Models in Healthcare"" <https://doi.org/10.18742/32076402>.
- NHS Wales 2026. "NHS Wales Solutions Exchange" <https://doi.org/https://gigcymru.github.io/Solutions-Exchange/index.html>.
- Nyaaba, M., M. SungEun, M. A. Apam, K. O. Acheampong, and E. Dwamena. 2025. "Optimizing Generative AI's Accuracy and Transparency in Inductive Thematic Analysis: A Human-AI Comparison". *arXiv preprint arXiv:2503.16485*.
- Robinson, S., R. E. Nance, R. J. Paul, M. Pidd, and S. J. Taylor. 2004. "Simulation Model Reuse: Definitions, Benefits and Obstacles". *Simulation modelling practice and theory* 12(7-8):479–494.
- Team SimPy 2024. "SimPy: Discrete Event Simulation for Python". *Team SimPy*.
- Tyler, J. M., B. J. Murch, C. Vasilakis, and R. M. Wood. 2022, June. "Improving Uptake of Simulation in Healthcare: User-Driven Development of an Open-source Tool for Modelling Patient Flow". *Journal of Simulation* 17(6):765–782.
- Ucar, I., B. Smeets, and A. Azcorra. 2019, July. "simmer: Discrete-Event Simulation for R". *Journal of Statistical Software* 90:1–30 <https://doi.org/10.18637/jss.v090.i02>.
- Uhrmacher, A. M., S. Brailsford, J. Liu, M. Rabe, and A. Tolk. 2016. "Panel—Reproducible Research in Discrete Event Dimulation—A Must or Rather a Maybe?". In *2016 Winter Simulation Conference (WSC)*, 1301–1315. IEEE.
- Yao, S., D. Yu, J. Zhao, I. Shafran, T. L. Griffiths, Y. Cao *et al.* 2023. "Tree of Thoughts: Deliberate Problem Solving with Large Language Models". *arXiv* <https://doi.org/https://arxiv.org/abs/2305.10601>.
- Zschaler, S., N. Mustafee, A. Harper, T. Monks, B. S. Onggo, C. S. Currie *et al.* 2025. "On Simulation Reuse in Healthcare Applications". *Simulation* <https://doi.org/https://doi.org/10.1177/00375497251383912>.

AUTHOR BIOGRAPHIES

LUCY MORGAN is an Analytics Manager in Simulation at The Strategy Unit within the NHS and an Honorary Researcher in the Department of Management Science at Lancaster University. Her research interests include health care simulation, model reuse and model uncertainty quantification. Her email address is lucy.morgan48@nhs.net.

ALISON HARPER is a Lecturer in Operations and Analytics at University of Exeter Business School. Her research interests include applied health and care research, reusable simulation models, real-time discrete-event simulation, and hybrid modeling. Her email address is a.l.harper@exeter.ac.uk.

THOMAS MONKS is an Associate Professor of Health Data Science at University of Exeter Medical School. His research interests include open science for computer simulation, urgent and emergency care, and real-time discrete-event simulation. His email address is t.m.w.monks@exeter.ac.uk.

AMY HEATHER is a Postdoctoral Research Associate at the University of Exeter working on the project STARS: *Sharing Tools and Artefacts for Reproducible and Reusable Simulations in healthcare*. She has developed guidance and tutorials on building reproducible discrete-event simulation workflows. Her email address is a.heather2@exeter.ac.uk.

STEFFEN ZSCHALER is a Reader in Software Engineering at King's College London. His research interests include software engineering for simulations, optimization, and digital twins, with a focus on healthcare applications. His email address is szschaler@acm.org.