EVALUATING THE FINANCIAL IMPACT OF MODELING AND SIMULATION IN HEALTHCARE: PROPOSED FRAMEWORK WITH A CASE STUDY

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ABSTRACT

Modeling and simulation have been widely used in health economics and health technology assessment for estimating long-term costs and benefits of health interventions. However, the implementation of simulation in the organizational planning of healthcare delivery is still limited and has not yet received the same level of engagement as it has in other industries. The purpose of this paper is to propose an analytic framework to quantify the value of modeling and simulation, so that the benefits can be evaluated more objectively by the healthcare stakeholders and can be compared across a broad range of health innovations. The application of the framework is illustrated in a case study of acute care for Ischemic stroke. Although the value of modeling and simulation can be measured in various forms, depending on the perspectives of stakeholders, this paper initially focuses on the financial value and takes the perspective of administrators who need to plan and manage health-care budgets.

1   INTRODUCTION

While there have been several systematic reviews of healthcare simulation and modeling (Fone et al. 2003; Katsaliaki and Mustafee 2010) which illuminate the challenges around modeling in healthcare, the question of value-for-money has not been systematically addressed. Summarizing the findings of this corpus of literature is not easy, because it has been growing at a rate of 30 publications per day (Brailsford et al. 2009). However, recent reviews have noted that only a small percentage (around 5-10%, depending upon definitions) relate to real-world scenarios (Brailsford et al. 2009, Jahangirian et al. 2012). In their analysis, Jahangirian et al. (2012) compared the percentage of conceptual papers and applied papers in three sectors and showed healthcare to be at a very different level of maturity from the military and manufacturing. Thus, an interesting situation exists where there is a buoyant literature where a high percentage of the papers are still about conceptual models or methods, while a limited percentage report impact.

There is also a rich literature around how to get the best out of simulation and modeling, and guidance on how to conduct healthcare-related research (Pidd 2009, Robinson 2008, Brailsford et al. 2013) However, the question of whether healthcare modeling and simulation represents better value-for-money than not modeling, or than using some other form of planning or design remains essentially unanswered. Chick and Gans (2009) have proposed a method that addresses aspects of economic evaluation.

Again, there are lots of narratives about the benefits of modeling, but merely reporting impact is not sufficient in healthcare. In engineering scenarios, the application of modeling methods is natural and the role of a model as a central piece of decision-making is well recognized. However, the impact of evidence-based medicine in healthcare has created an expectation that decision-makers will have evidence in support of decisions. Also, there is an expectation of a balanced study with some suitable comparator and, with decades of research since Cochrane put clinical trials onto a formal footing, the quality of evidence in healthcare is extremely high at its best, elevating the expectations made of non-medical

interventions significantly. In most medical hierarchies or evidence, simulation and modeling do not feature highly.

Given the powerful use of modeling and simulation in other fields, the question arises what role the simulation and modeling could or should play in healthcare. In the medical mindset, this usually means a cost-effectiveness analysis where modeling and simulation could be shown to represent better outcomes per unit expenditure than other interventions. In clinical practice this is a well-understood model, but applying it to intangibles such as the knowledge derived from statistical models is more complicated.

Modeling is used extensively as part of economic evaluations, often in the form of Markov models and decision-trees. However, the value of those models in the evaluation process is not subject to evaluation. At the Cumberland Initiative, we have been sensitive to the absence of formal repositories of strong evidence in favor of modeling. We held an event – the Festival of Evidence – to gather the various types of evidence in support of these methods and to understand how best to use them. The resulting report (Brailsford and Klein, to be published) assesses many of the issues around the nature of evidence and reports on many impact stories.

In this paper we plan to take the state of the situation further. We propose a method that will appeal to a clinical view of evidence by proposing a framework in which economic impact can be assessed for comparative analysis when considering whether to model or not. The basic criteria here are that the method should be robust and that the evidence should be readily obtained.

2   METHODOLOGY

We present an analytic framework to quantify the value of modeling and simulation. We aim to enable more objective evaluation of their benefits by healthcare stakeholders and to enable comparison across a broad range of health innovations. Although the value of modeling and simulation can be measured in various forms (e.g. number of lives saved, specific health outcomes, systems' efficiency and productivity, patient experiences, etc.), depending on the perspectives of stakeholders, this paper focuses on the financial value and takes the perspective of administrators who need to plan and manage health-care budgets. This includes, but is not limited to, administrators of national or regional health-care programs, administrators of accountable care organizations, and administrators of private insurance plans.

The proposed framework is adapted from the budget impact analysis used in health technology assessment (Mauskopf et al. 2007). It aims to compare the healthcare environment before and after the implementation of modeling and simulation. Any changes in the healthcare setting contributed by the use of modeling and simulation -- such as the changes in care pathway and resources used -- are translated into short- and long-term financial consequences.

Figure 1 presents the general model of this analytic framework. The total population at risk should be all patients potentially affected by the changes induced by modeling and simulation. The disease condition of interest, its treatment, care pathway, and outcomes should be clearly described in the analysis. The time horizon for the analysis and the perspective from which the analysis is conducted should be clearly specified. It is recommended that the perspective is that of a decision maker who is responsible for healthcare budgeting. The time horizon should correspond to the budgeting time horizon, which is usually annual. However, a longer time horizon might be needed to incorporate all health-care costs related to a chronic health condition.

The size of the population with the disease condition is estimated by multiplying the total population at risk by the incidence rate of the disease. Ideally, this incidence rate should be estimated from epidemiological data in the decision maker's population potentially affected by the modeling and simulation. However, if this data is not readily available, the incidence rate obtained from a nationally representative population, adjusted for the risk factors of the decision-maker's population, can also be used. It is assumed that the population with the disease condition is divided into two subgroups. A group of patients receiving proper diagnosis and treatment in a timely manner is called *Treated Population* subgroup, and the remaining patients are considered the *Untreated Population* subgroup. The use and costs of health-care services are estimated for both subgroups over the time horizon of the analysis. The

resource use and costs must be the ones relevant to the perspective of decision-maker and the disease condition only. The total costs of illness combine all the healthcare costs from both subgroups.
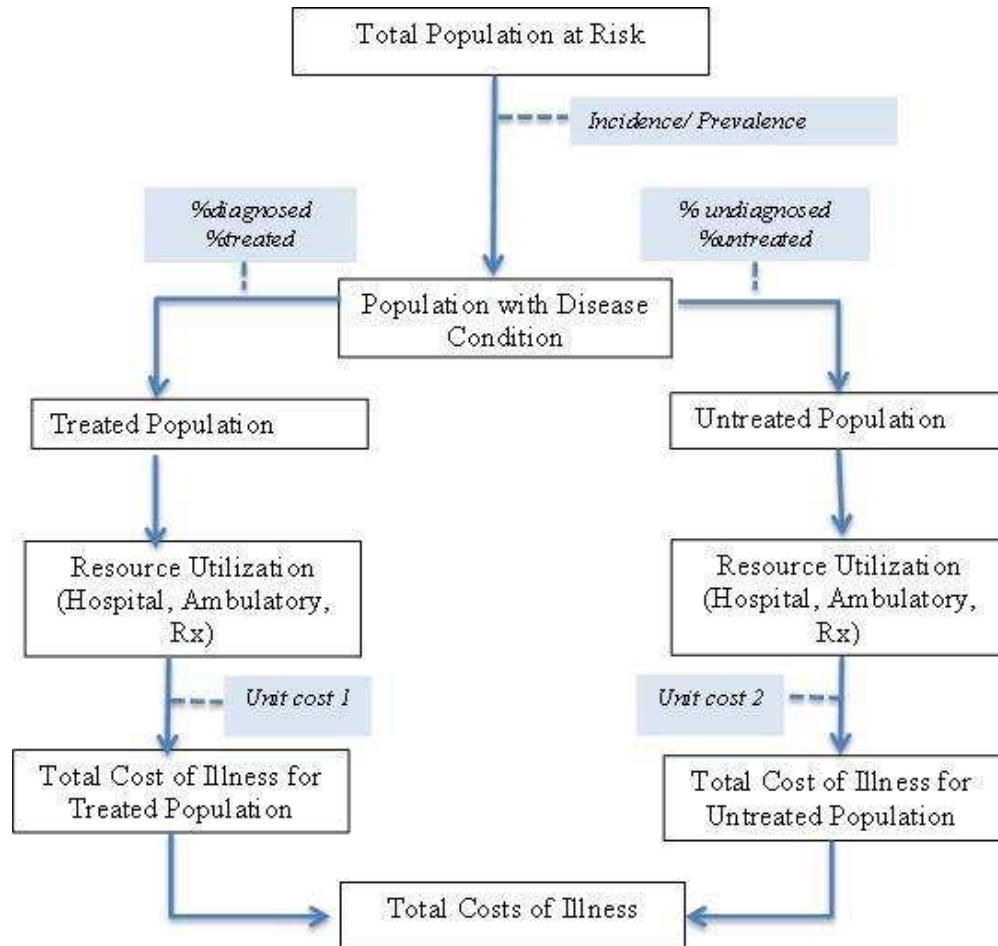

Figure 1: Financial impact framework.

The changes in the healthcare setting resulting from the implementation of modeling and simulation are represented by the changes in one or more model parameter values. For example, one scenario could be that the use of modeling and simulation helps improve the efficiency of health-service delivery and hence increases the percentage of patients receiving proper diagnosis and treatment, and/or reduce resource utilization (e.g. shorten the hospital stay). The total costs of illness computed with and without incorporating these changes are referred to as *After-Simulation* and *Before-Simulation* total costs respectively. The financial impact attributable to modeling and simulation is calculated as the difference between these two total costs.

3   CASE STUDY

We apply the financial impact framework to a case of acute care for Ischemic stroke. Ischemic strokes are caused by blood clot in an artery leading to the brain. *Thrombolysis*, also referred to as '*rt-PA*' and '*alteplase*', is a clot-busting treatment to dissolve the clot and restore blood flow. It has been licensed for the treatment of acute Ischemic stroke worldwide, and is the only licensed treatment for Ischemic stroke in the UK. If eligible for the treatment, patients treated with thrombolysis have significantly less risk of developing a disability after stroke and better overall health outcomes (Hacke et al. 2004). The benefit of

the treatment depends markedly on the time between stroke onset and start of treatment (OTT) (Lees et al. 2010). It is most effective if given within 3 hours of symptom onset. In UK, the treatment is licensed for up to 4.5 hours (Stroke Association 2015).

Delays in the acute stroke care pathway will significantly affect the thrombolysis rate, i.e., percentage of patients receiving thrombolysis (Monks et al. 2012, Penaloza-Ramos et al. 2014). Several studies have been conducted to determine strategies to optimize the acute care pathway and hence reduce the time to treatment (Monks et al. 2012, Penaloza-Ramos et al. 2014). Monks et al. (2012) used a discrete-event simulation model to investigate the most effective ways to increase thrombolysis rate. More details of the study and results are provided in Section 3.2.

3.1 Acute Care Pathway for Stroke

In the UK, the NHS and Public Health England use the FAST acronym in public health awareness campaigns: **f**ace, **a**rms, **s**peech: **t**ime to get help. People showing symptoms have three routes to hospital – through their general practitioner (GP, approximately equivalent to a primary care physician), or by ambulance or self-referral at the Emergency Department. The system varies in the UK, with the emergence of Urgent Care Centers and some direct admission stroke wards.
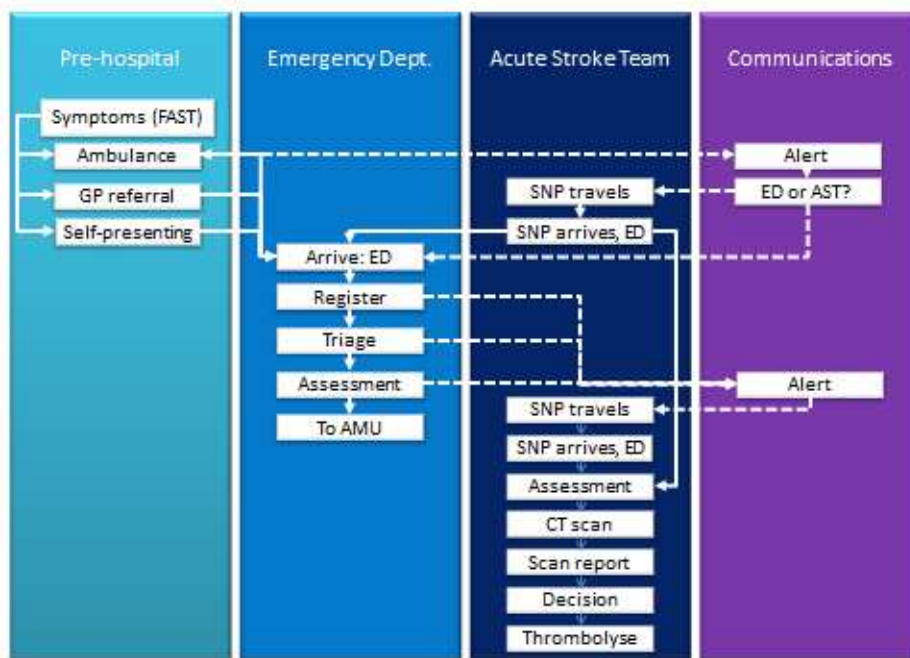

Figure 2: Acute care pathway (after Monks et al. 2012).

To try to evaluate the effectiveness of modeling, we refer to a case that describes a change in pathway design as a result of modeling (Monks et al. 2012). This case describes a modeling study in which a Discrete Event Simulation (DES) model was used to model a pathway and then recommend changes, which were then implemented. That study reports on a series of benefits that resulted. Here we analyze some of those benefits in economic terms.

As shown in figure 2, the patient travels to the emergency department (ED). This follows the pathway described by Monks et al. (2012) and shows activity in four categories: outside the hospital, in the ED, by the acute stroke team and in the ether, as electronic and radio signals connect the various parties involved. If the patient is arriving by ambulance, the crew may signal ahead and a decision may

be made (right hand column) to involve the acute stroke team. If so, a stroke nurse practitioner (SNP) will go to the ED. If the acute stroke team has not been engaged, the patient will be registered, triaged and assessed. At any of these stages, an alert may summon a stroke nurse practitioner.

Once engaged, the acute stroke team will take over the pathway, as shown in Figure 2, assessing the patient, organizing a prioritized scan, receiving a radiologist's report, making a decision and then, if appropriate, initializing thrombolysis. As noted, there the problem that those with hemorrhagic strokes, may suffer if thrombolysed, but the best medical opinion is in favor of managing that risk and in line with the guidelines cited above.

The key elements of the assessment we present are around the time needed to reach an effective decision point, namely, the time taken to do so and the number of people that can receive thrombolysis as a result of streamlining the pathway in line with the DES model.

3.2 Simulation Impacts

Monks et al. (2012) used a discrete simulation to model the emergency stroke care at a district hospital in UK. The model was then used to explore different alternatives to maximize the benefits of thrombolysis. Based on the simulation results, recommendations were made to change the care pathway to improve thrombolysis rate and to reduce the time to treatment. In the follow-up study (Monks et al. 2015), the implementation and evaluation of the changes informed by the simulation were conducted in the real-world setting. The study showed that the changes recommended by the simulation lead to the increase in the thrombolysis rate by 3.1% (95% CI 1.3%-4.7%). During the late stage of their implementation and evaluation, the hospital achieves the highest thrombolysis rate of 14.5% overall. The study also reported the reduction in the average time from patients' arrival to treatment.

3.3 Financial Impact Model

Our model focuses on analyzing the financial impact of the simulation and modeling. It takes the perspective of a National Health Service (NHS) funded hospital and assumes one-year time horizon. The model is developed in Microsoft Excel spreadsheets (with VBA macros) with design goals of being transparent, user-friendly, and usable by cross-disciplinary collaborators.

In our study, the *Before-Simulation* scenario refers to the hospital operation and its outcomes before the implementation of the changes recommended by the simulation. The *After-Simulation* scenario refers to the operation and outcomes after the changes were implemented. Combining the results from Monks et al. (2015) and the thrombolysis efficacy data from Lees et al. (2010), the numbers of patients with and without stroke-related disability, referred to as *disabled and not-disabled survivors*, are estimated in the Before-Simulation and After-Simulation scenarios. The differences in the numbers of disabled and not-disabled survivors between both scenarios are, in turn, converted to the difference in the healthcare resource uses and costs.

3.3.1 Model Parameters

Tables 1-2 list the parameter values used in the model. One of the key parameters of the model is the size of the population at risk. In the case study, this is the number of patients arriving with stroke at a hospital. The higher the number of stroke cases at a hospital, the higher the financial impacts. This number could vary greatly between hospitals. According to the national statistics, stroke occurs approximately 152,000 times a year in the UK (Stroke Association 2015). There are approximately 150 NHS hospitals. Hence, we assume that the number of strokes at a hospital is approximately 1,000 cases per year. However, according to Monks et al. (2012), the number was estimated at 600 stroke cases per year.

Another key information for the model is the percentages of patients with different OTTs in the Before- and After-Simulation scenarios. Most importantly, the percentage of patients with OTT of less than 3 hours, the 'effective' period for the treatment. Since the data is not available, we assume 60% of patients having OTT of less than 3 hours. In the base-case analysis, we make a conservative assumption

that the use of simulation does not improve this percentage, and the value of 60% is used in both Before- and After- Simulation scenarios.

3.3.2 Efficacy of Thrombolysis and Estimation of Number of Disabled and Not-Disabled Survivors.

Lees et al. (2010) analyzed the efficacy of thrombolysis in treating patients with ischemic stroke and its relationship to OTT. The health outcomes were measured in terms of the disability levels up to 3 months after the stroke onset. The disability level was measured by a Modified Rankin Scale (MRS) score which ranges from 0 to 6. The score of 0 or 1 indicate no or not-significant disability, 2 indicates slight disability but able to look after own affairs without assistance, 3 to 5 indicate moderate to severe disability and nursing care required, 6 indicates death.

Based on the results from Lees et al., the percentages of patients by MRS scores can be calculated in the cases when patients receive thrombolysis within 3 hours of onset, when patients receive thrombolysis in more than 3 hours of onset, and when patients do not receive thrombolysis (placebo). Table 1 shows the results of this calculation. Combining the efficacy results from Lees et al. (2010). and the thrombolysis rate results from Monks et al. (2015) study, the number of disabled (MRS scores of 3-5) survivors, the number of not-disabled (MRS scores of 0-2) survivors, and the number of deaths are estimated in the Before- and After-Simulation scenarios. The adverse event of the thrombolysis is that it increases the risk of intracerebral hemorrhage, which could lead to death. These adverse health outcomes are not accounted for in the financial impact analysis. We estimate the number of deaths and the number of intracerebral hemorrhage cases and report them in a separate table.

3.3.3 Resource Use and Unit Costs of Healthcare Services

Table 2 also shows the cost data (in their original price year) used in our analysis. All cost data are given in Great Britain Pounds (GBP) and are adjusted to a price year of 2014 using consumer price indices (The Office of National Statistics 2015). Costs included in the model are the costs of implementing thrombolysis, the costs of rehabilitation, and the costs of long-term care for not-disabled and disabled survivors. The cost of acute care of stroke is not included in the model. Since we assume the same number of patients with stroke arriving at a hospital in the *Before-* and *After- Simulation* scenarios, the total costs of acute care of stroke would be the same in both scenarios.

Although the numbers of disabled and not-disabled survivors are estimated over one-year time horizon, the long-term care costs need to be accumulated for a longer period in order to include the complete information about the financial consequences. Hence, the costs of long-term care for disabled and non-disabled patients are computed for 1, 2 and 5 years and are discounted by 3.5% annual rate (as suggested by NICE guideline).

The drug costs of thrombolysis were estimated at £480 (Sandercock et al. 2004). The additional resources required to deliver thrombolysis vary significantly across the UK (Sandercock et al. 2004) and a good estimate for the total cost of implementing thrombolysis is not available. The estimated total cost of £1000 from Sandercock et al. 2004 is used in our analysis.

Table 1: Percentages of Patients by Modified Rankin Scale (MRS) Score at 90 days and by the Time from Stroke Onset to Start of Treatment (OTT) Interval.

	MRS 0-1	MRS 2	MRS 3-5	Mortality	Intracerebral Hemorrhage
Patients receiving thrombolysis, OTT 0-3 hours	41.81%	7.56%	33.17%	17.46%	34.70%
Patients receiving thrombolysis,	41.62%	12.78%	32.96%	12.64%	30.28%

OTT 3-6 hours					
Patients not receiving thrombolysis (Placebo)	34.85%	12.42%	40.80%	11.93%	24.24%

3.4 Preliminary Results

Table 3 presents the results when the analysis is done using the base-case values in Table 2.

Table 2: Model Parameters.

	Base-Case	Sampling Distribution (range)	Reference
Number of patients arriving with acute stroke per year at a hospital	1000	-	Assumption
Among patients with acute stroke, percentage of those having ischemic stroke	89%	-	Penaloza-Ramos et al. (2014)
Thrombolysis rate in the *Before-Simulation* scenario	3.8%	Triangular (3.5%, 5%)	Monks et al. (2015)
Increase in the thrombolysis rate in the *After-Simulation* Scenario	3.1%	Triangular (1.3%, 4.7%)	Monks et al. (2015)
Among patients receiving thrombolysis, percentage of those with OTT of less than 3 hours in the *Before-Simulation* scenario	60%	-	Assumption
Increase in the percentage of patients with OTT of less than 3 hours in the *After-Simulation* scenario	0%	Deterministic 0%-40%	Assumption
Cost of implementing thrombolysis treatment (in 2000£)	£1000	Triangular (with ± 50% range)	Sandercock et al. (2004)
Ambulatory rehabilitation (in 1996 £) Not-Disabled Survivor Disabled Survivor	£38 £718	Triangular (with ± 50% range)	Chambers, Koch, and Hutton (2002); Sandercock et al. (2004)
Long-term care cost per year (in 1996 £) Not-Disabled Survivor Disabled Survivor	£824 £10,632	Triangular (with ± 50% range)	Chambers, Koch, and Hutton (2002); Sandercock et al. (2004)
Consumer price index (overall): year 2014	128.00	-	The Office for National Statistics (2015)
Consumer price index (overall): year 2000	93.1	-	
Consumer price index (overall): year 1996	88.10	-	
Annual discount rate for long-term care costs	3.5%	-	NICE 2012

The total cost of care includes the cost of implementing thrombolysis, the cost of rehabilitation, and the cost of long-term care for disabled- and not-disabled survivors. For a hospital with 1,000 stroke cases per year (or 890 ischemic stroke cases per year), the changes recommended by the simulation study lead to a cost-saving only when the long-term cost of care is considered for more than one year. This is to be expected since more patients receive thrombolysis, the total cost of treatment to the hospital increases. However, the cost increase is offset by the saving of the long-term cost of care. It is estimated that the use

of simulation leads to the saving in the total cost of care of £27,534 when the long-term cost of care is considered over a two-year period, and £114,674 for a five-year period.

Table 3: Base-case results.

	Before-Simulation	After-Simulation	Cost-Saving
Total cost of care; long-term costs of care projected over 1 year	£6,519,653.69	£6,523,222.85	-£3,569.16 (Not Cost-Saving)
Total cost of care; long-term costs of care projected over 2 years	£12,388,061.81	£12,360,527.62	£27,534.19
Total cost of care; long-term cost of care projected over 5 years	£28,829,211.01	£28,714,536.55	£114,674.46

The financial impact analysis does not include the health outcomes explicitly -- they are typically accounted for in terms of the healthcare cost. However, the adverse effect of thrombolysis is not accounted for in the cost calculation. One of the main adverse events of thrombolysis is that it could increase the risk of intracerebral hemorrhage, which could lead to death. In the base case analysis, the number of deaths and the number of intracerebral hemorrhages increase slightly in the After-Simulation scenario (Table 4).

Table 4: Mortality and Intracerebral Hemorrhage Cases (Base-Case Analysis).

	Before-Simulation	After-Simulation
Number of deaths	107.39	109.57
Number of intracerebral hemorrhage cases	218.71	222.19

Table 5: Probabilistic Sensitivity Analysis (10,000 iterations).

	Mean (Standard Error)
Cost-Saving Estimates; when the long-term costs of care is estimated over 1 year	-£3,866.00 (£112.76)
Cost-Saving Estimates; when the long-term costs of care is estimated over 2 years	£29,369.70 (£178.59)
Cost-Saving Estimates; when the long-term costs of care is estimated over 5 years	£122,484.05 (£447.48)

We use Monte Carlo sampling to explore the effect of parameter uncertainty on the cost-saving results. We assume triangular distribution for all parameters, with the mode equal to the base-case value and the range given in the third column of Table 2. The model is run for 10,000 iterations. Table 5 presents the simulated estimates of the mean and the standard errors.

In the base-case analysis, it is assumed that simulation only improves the thrombolysis rate but does not increase the percentage of patients receiving the treatment within 3 hours from the stroke onset. This is a rather conservative assumption since, in the evaluation study by Monks et al. (2015), the use of simulation also reduced the time to treatment for patients. We explore different scenarios by varying the

percentage of patients with OTT of less than 3 hours in the After-Simulation scenario from 60% to 100% (i.e. the increase of 0% to 40% from the base-case percentage in Before-Simulation scenario). Results are shown in Figure 3. The method of common random numbers was used for the all scenarios.
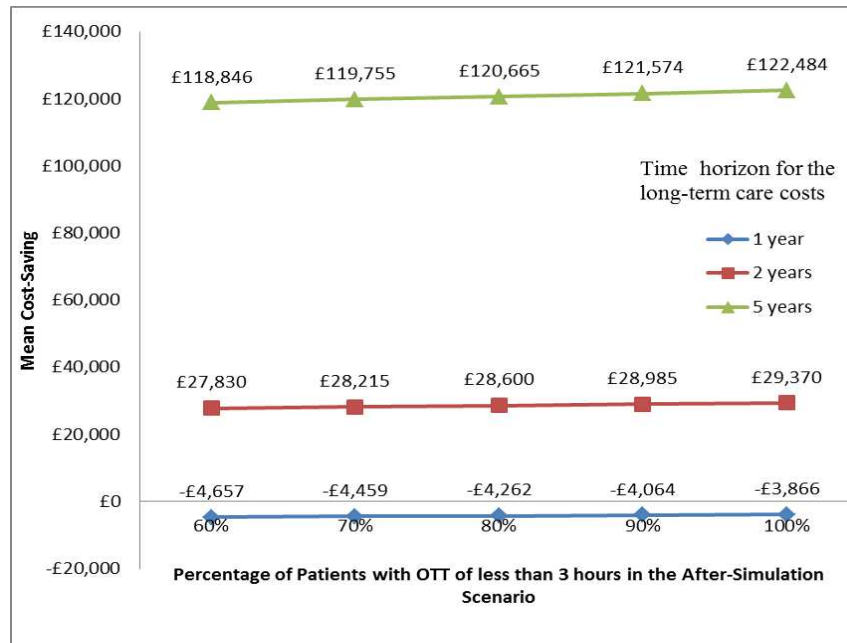

Figure 3: Scenario Analysis on the Improvement of the Percentage of Patients with OTT of less than 3 hours in the After-Simulation scenario.

4   CONCLUSIONS AND FUTURE WORK

We report an analysis to understand the value of modeling and simulation in economic terms and to start to put healthcare modeling on a similar footing to those of other interventions.

This financial impact analysis is adapted from the budget-impact analysis framework. In such framework, the health outcomes are not assessed explicitly but rather accounted for in terms of the healthcare costs. So, as the first stage on the journey, this analysis is primarily about cost benefits and does not yet represent a full cost-effectiveness study, where the health states of all the patients would also have been assessed. The ultimate aim of such analysis is two-fold:

- To be able to justify the use of modeling to clinical teams interested in practicing evidence base medicine and, as part of this,
- To be able to assess organizational interventions based on modeling alongside other options (e.g. in this case, the use of a different thrombobising agent).

This case study is also an example of how economic analysis may be conducted using studies already in the public domain. Thus, an important aspect of the study has been to take a modeling study reported in terms familiar to the healthcare community, and to wrap the economic evaluation around it.

There are clearly many ways in which this work can be developed. As noted, a full economic evaluation would require the health states of patient cohorts to be estimated. This analysis would also require an estimate of the cost of the intervention and the cost of the modeling within that intervention. Quite how much of the benefits are associated with the modeling itself is still something of an open question, although one way to answer it would be to compare the use of modeling to redesign the system with other options (expert opinion, play-do-study-act cycles, for instance).

However, even within the limitations of the current study, the analysis will support a number of important discussion with decision makers. For instance, the analysis could already be used to discuss what threshold of effectiveness would be needed of a model in order for it to contribute to pathway redesign.

The main conclusions are that first-stage economic assessment of the value of modeling in healthcare is viable and would confer benefits to the modeling exercises being undertaken and would probably support the wider adoption of modeling and simulation as methods of designing interventions in clinical environments. These methods can also help modelers understand the constraints (particularly of cost and time and quality of results) under which modeling can represent value-for-money to clinical customers. In addition, modeling can be used to support a range of discussions with clinical decision-makers around the relative costs and benefits of elements of patient pathways.

Clearly, there is a long way to go and the modeling lobby can learn a lot from the evidence-based medicine community in terms of building robust cases for inclusion in the toolset of healthcare decision makers.

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