# A discrete event simulation model of a hospital for prediction of the impact of delayed discharge

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# A DISCRETE EVENT SIMULATION MODEL OF A HOSPITAL FOR PREDICTION OF THE IMPACT OF DELAYED DISCHARGE

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## ABSTRACT

Patients who have additional care needs after a stay in hospital can often experience delays in being discharged. These delayed discharges and their impact on the smooth running of hospitals has been well publicised in the UK in recent years. In this preliminary work, we build a discrete event simulation model to describe the process of a patient leaving the hospital. Based on a proposed plan for Southampton, we investigate the impact of providing intermediate care in the form of Discharge to Assess places on the number of patients who remain in hospital longer than necessary. We describe the model, a sensitivity analysis and preliminary results.

**Keywords:**

Discrete Event Simulation, Delayed discharge, Social care, Hospital

## 1 INTRODUCTION

Recent work from the Nuffield Trust shows that delayed discharges in the UK increased by 57% between April 2021 and April 2022 (Flinders and Scobie 2022). In Scotland, the media have highlighted that one in six patients should not be in hospital, and consequently Accident & Emergency Waiting times are at a record high (BBC News 2022). A delayed discharge or 'delayed transfer of care' (DTOC) is defined to be one that occurs after a patient is medically optimised for discharge (The King's Fund 2018). Such delays are bad for patient outcomes as longer stays in hospital tend to result in longer recovery times or even an irrecoverable deterioration in health (Rojas-García et al. 2018). But they are also problematic for hospitals by limiting the number of beds they have available for new patients. The reasons for the delays appear to be largely due to problems in the social care sector which have led to a lack of availability of the care needed. We do not consider here how to improve availability in the social care sector but instead focus on modelling the use of what is described as a Discharge to Assess (D2A) process (NHS Improvement 2022), a form of intermediate care between the hospital and social care which we describe below. This allows us to investigate how varying the number of places available in this intermediate process will affect the number of patients with a delayed discharge and the number of hospital bed days being used for patients who are medically optimised for discharge but unable to leave.

We consider the specific case of University Hospital Southampton (UHS) in this preliminary work which wrote and published a plan for a discharge process in Schofield (2021). This describes two options for D2A: using private care home beds outside of the hospital and a ward in a smaller community hospital for what we describe as inpatient D2A, or alternatively the Home First scheme whereby patients are sent home with some care provision. In both cases patients are assessed for their longer term care needs during their time in D2A with one of the stated aims being the provision of more long term care taking place at home. We use the simulation model to determine the impact of changing the number of available D2A places on the key measures of the number of delayed discharges and the number of extra bed days being used by patients who are medically optimised for discharge.

This work aims to make contributions by: (i) modelling the flow of patients to both intermediate and long term care in the UK NHS, and (ii) modelling delayed discharge using an acceptance probability to represent the situations where a delayed transfer of care occurs due to reasons other than capacity constraints (e.g., a disagreement with the patient's family about the care placement). This paper is applied to the Southampton context, but future iterations of the work will consider a reusable model that can be applied to multiple settings.

We discuss previous work in this area in Section 2 before providing a more detailed problem description and details of the DES model in Section 3. Preliminary results are given in Section 4 before we conclude and describe our plans for future work.

## 2 LITERATURE REVIEW

Discrete event simulation (DES) models the operation of a system as a sequence of events in discrete time. It has been used extensively to model patient flow through components of healthcare systems internationally (Mustafee et al. 2010). There are many models of individual hospital units, for example emergency departments and intensive care units, however it is recognised that models of individual units developed in isolation of the wider healthcare system may not appropriately account for blockages further downstream (Salmon et al. 2018). For example, overcrowded emergency departments and queues of ambulances outside hospitals are often the most visible symptom of delays in discharging patients from in-patient hospital to the community care (Kelen et al. 2021). This section presents a literature review in respect of papers which use simulation modelling to consider the problem of delayed discharge from in-patient hospital care to community care facilities.

Tobail et al. (2013) used value stream mapping and discrete event simulation (DES) to show that length of stay and bed availability could be improved by reducing the rate of late discharges from hospital. Khanna et al. (2016) developed a DES of an Australian hospital to experiment with the impact of various hospital discharge policies on length of stay, hospital occupancy, and emergency department overcrowding. The study highlighted that improvements to hospital patient flow could be achieved by discharging patients early in the day and by spreading discharges across the day. Busby and Carter (2017) built a generic DES to assess hospital-wide bed management strategies, which include expedited discharge from hospital. Qin et al. (2017) developed a comprehensive DES of an Australian hospital which captured patient flow from emergency department arrival to hospital discharge. The authors used scenario experimentation to determine the impact of various hospital discharge strategies (e.g., patients can be discharged at any time of the day or length of stay can be reduced by 12 hours) on overall hospital occupancy. Although each of these four studies experimented with changes to hospital discharge policies, they did not model the link between hospitals to community care, so the logistics of discharging patients and the capacity constraints within downstream community care facilities were not considered.

The number of studies which have used simulation to model the flow of patients between in-patient hospital and community care are limited as highlighted in Patrick et al. (2015) and Harper et al. (2021). Zhang et al. (2012) combined simulation, optimisation, and survival analysis to develop a model for planning long-term care capacity in British Columbia, Canada. The model was used to find the minimum capacity level needed each year to satisfy a waiting time threshold. Patrick et al. (2015) developed a DES of patient flow between hospital and the community to long-term care homes in a region of Canada. The model included patient preferences and was treated as an inventory management problem. Both studies modelled capacity as the total number of beds in community care facilities.

Focusing on modelling the link between hospital and 'step down' home-based intermediate care, Harper et al. (2021) used DES to model the patient pathway from hospital discharge to community visits in the UK. The model was designed such that patients could transition from hospital to step-down community care if there was sufficient capacity (defined as the number of community visits). If no community visits were available, the patient would wait in hospital until capacity became available, representing a delayed discharge. The authors used the DES model to determine an optimal capacity of step-down care, which minimised cost of delayed discharge and the cost of under-utilised community care services. Onen-Dumlu et al. (2022) extended this work to model the flow between hospital and three types of step-down intermediate community care in the UK NHS. The objective of this study was to determine an appropriate level of intermediate community care capacity in the context of the COVID-19 pandemic. In both of these papers, capacity was modelled as the total number of community care visits.

Some of the papers reviewed in this section have experimented with improving patient flow by changing hospital discharge policies; these studies make an assumption that downstream community care facilities are not capacity constrained. Other papers have modelled the capacity of community care as the number of available beds or visits. The assumption that patients can be discharged if a bed becomes available in community care is a limitation of these models. Patients cannot always be moved even if there is an available bed in community care, due to reasons such as (i) disagreements with patients and families about the care placement, (ii) funding problems, (iii) housing issues, and (iv) waits for equipment to be installed (The King's Fund 2018).

This paper addresses a gap in the literature by viewing the problem of delayed hospital discharge as multifaceted, rather than directly related to capacity, where the availability of community care placements are modelled using an acceptance probability. This study is also novel in that it considers flow of patients to both intermediate and long term care in the UK NHS.

## 3 METHODOLOGY

### 3.1 Problem Description

Our focus is on modelling the impact of different resourcing on the number of patients who are medically optimised for discharge but remain in hospital. As a result, we do not explicitly model the hospital stay or difficulties accessing hospital care. Only patients who need care after a stay in hospital enter the model and patients leave the model when they are directed to a care provider. We use the proposal in Schofield (2021) as a guide to the pathways through the hospital and care systems, which are shown in Figure 1. We discuss these in more detail below.

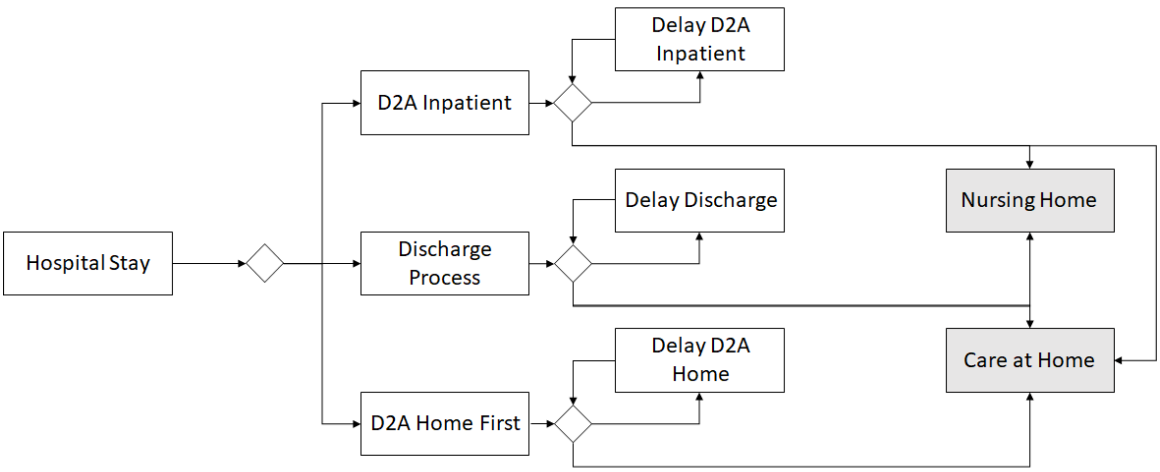


Figure 1: A conceptual model of the delayed discharge simulation.

Following completion of hospital treatment, patients will start one of three processes:

1. Move to a *Discharge to Assess* ward run by the hospital (D2A Inpatient) in which their needs will be assessed and from which they will be sent to either a nursing home or to their own home with some care, labelled as care at home. Within Southampton, these D2A beds are community rehabilitation beds at a neighbouring hospital (the Royal South Hants) and interim beds that have been contracted from the nursing home market.
2. Move home and follow a *Discharge to Assess* process at home (D2A Home) before being set up with care at home.
3. Follow a discharge process while remaining in the hospital. This is the least preferred option and patients will only follow this path if there is no availability in the relevant D2A activity (either inpatient or at home).

Following completion of the D2A process either as an inpatient or at home or following completion of the hospital discharge process, patients will try to access the care that they need. Rather than explicitly modelling capacity of care places, we instead assume that there is a probability that a patient will be given a care place. As Figure 1 shows, if patients are unable to access a nursing home place or care at home they enter a delay state. Delay states are assumed to have a fixed duration of 1 day, assuming that staff will not repeatedly make enquiries of the same care providers during one day for a particular patient.

### 3.2 Simulation Model

The simulation model is built in Simul8 and follows the process displayed in Figure 1 where Nursing Home and Care at Home are included as exit points. Patients enter the model when they are assumed medically fit for discharge rather than when they enter the hospital.

There are two key metrics for the model: the number of days that patients are delayed before accessing care and the number of patients who are medically fit for discharge and are still in hospital. We may also be interested in the utilisation of the D2A activities and whether patients are being blocked from leaving them because of an inability to access nursing home or care at home places. The number of days a patient spends in either a D2A bed or a hospital bed after being declared ready for discharge can be measured by counting the number of times they enter the delay state. We can also count the number of patients in the Delay Discharge state to provide an estimate of the number of patients in hospital who are medically fit for discharge. Similar results can be collected for the two Delay D2A states.

In order to limit the capacity in D2A Inpatient and D2A Home we use two resources: D2A Inpatient Resource and D2A Home Resource that are needed in both the actual state and the delay state. This ensures that patients will only enter D2A states when there are spaces available. If there are no spaces available when they enter the model they start the discharge process in hospital and approach the nursing home or care at home directly following a discharge process. We assume an unlimited capacity for the Delay Discharge state.

Patients are given a label when they enter the model which indicates whether they will need either a nursing home bed or care at home. This affects their routing: patients who are labelled as needing a care home bed will only be allowed to enter D2A Inpatient or the Discharge Process. Patients labelled as needing care at home are currently only able to enter D2A Home and the Discharge Process but in future versions of the model we will experiment with allowing these patients to also enter D2A Inpatient.

As the model is in its early stages we have not made it publicly available but subsequent work will translate the Simul8 model into SimPy to allow for more straightforward experimentation and easier sharing.

### 3.3 Parameterisation

A full set of parameters is given in Table 1. The scenario we include here is based on University Hospital Southampton (UHS) and estimated from Schofield (2021). We provide further details below.

UHS received 154,350 admissions in 2021-22 in the most recently published Hospital Episode Statistics for England (NHS Digital 2022). Of these, the percentage needing some form of care is estimated as 27% (Schofield 2021), 5% needing a nursing home and 22% needing care at home.

Table 1: Simulation model parameters.

| Parameter | Distribution |
|---|---|
| Arrival rate (number of patients becoming ready for care per day) | Poisson(114) |
| Percentage given nursing home label | 18.52% |
| Percentage given care at home label | 81.48% |
| Duration in D2A Inpatient | 1 day (fixed) |
| Duration in D2A Home | 1 day (fixed) |
| Duration in hospital discharge process | 1 day (fixed) |
| Probability of acceptance at a nursing home (per day) | 1/7 |
| Probability of acceptance for care at home (per day) | 1/3 |
| Number of beds available in D2A Inpatient | 75 |
| Number of spaces available in D2A Home | Varied in Table 2 |
| Number of spaces available in Delay Discharge | Unlimited |

Assuming that arrivals are spread evenly over the year, this gives an overall arrival rate of 114 per day with 18.52% of patients entering the model requiring a nursing home place and the remainder requiring care at home.

The duration of time spent in the D2A states and in the hospital discharge state before being ready for discharge is currently set to 1 day. We are aware that this may not be the correct duration to use and future work will investigate different public datasets to enable a better estimate of this variable.

We can derive a probability of acceptance $p$ from the expected time spent waiting for a place using the result that

$$\text{Expected time spent waiting} = p\sum_{i=1}^{\infty} i(1-p)^i = 1/p.$$

Therefore, using an expected time spent waiting for a nursing home bed of 7 days and for care at home of 3 days, we use $p = 1/7$ and $p = 1/3$ respectively.

Based on Schofield (2021) we assume 75 beds are available in the D2A inpatient wards. No details are given on the capacity of D2A home and consequently we experiment with different values in the results section to determine an appropriate value to use in order to reproduce published statistics for UHS. We do not put a limit on the number of spaces available in Discharge Process and Delay Discharge and instead experiment with how high this number gets under different scenarios.

### 3.4 Model Verification and Sensitivity Analysis

Model verification was performed to ensure that the conceptual model in Figure 1 was correctly translated into the Simul8 model shown in Figure 2. This was achieved by maintaining documentation, performing sensitivity analysis to check the model behaved as expected, and using Simul8's graphical interface to check the flow of entities through the model.

The model outputs of interest are the *number of days that patients are delayed before accessing care* and *the number of patients who are medically fit for discharge but remain in hospital*. An initial validation was conducted to compare the model output with information on delayed transfers of care at UHS using data from NHS England (2022) on the number of patients in hospital who no longer meet the criteria to reside and the number of additional bed days for patients with a length of stay of 7+, 14+ and 21+ days.

Preliminary results are presented in Section 4. The model was run 5 times for each of the scenarios presented. All of the results are presented with 95% confidence intervals. The results were calculated using 1 year of simulated time with a warm-up period of 8 weeks. This was determined to be appropriate by visual inspection of the model outputs.

Sensitivity analysis was conducted to (i) determine an appropriate level of capacity in the D2A Home resource, (ii) experiment with the probability of acceptance at a nursing home, and (iii) experiment with the probability of acceptance for care at home. Scenario analysis was carried out to investigate the impact of introducing additional D2A Inpatient beds.

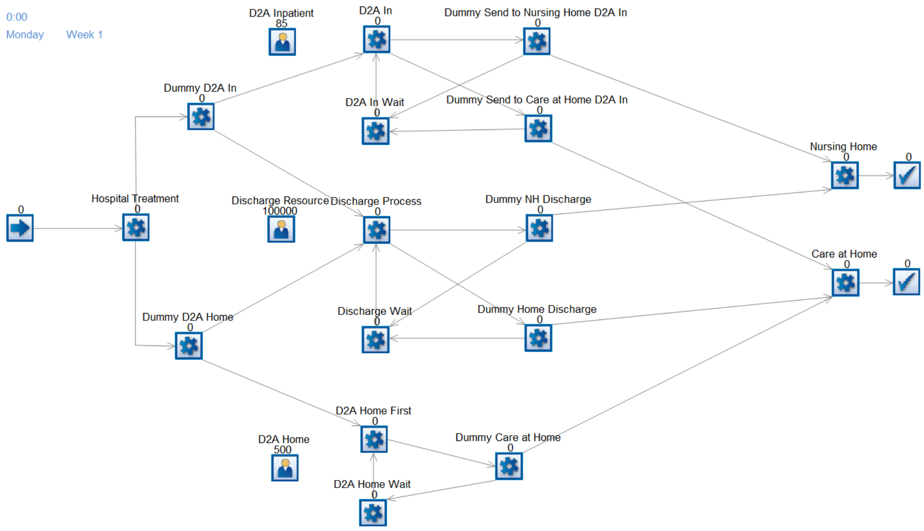


Figure 2: Screenshot of the SIMUL8 Model.

## 4 PRELIMINARY RESULTS

### 4.1 Determining an Appropriate Capacity of the D2A Home Resource

The first set of experiments presented in Table 2 were conducted to determine an appropriate capacity of the D2A Home resource. The simulation model was run with the parameter settings listed in Table 1 with D2A Home varied from a capacity of 350 to 650. The model output shows that the average number of patients delayed in hospital decreased as the capacity of the D2A resource was increased. The model output was closest to the NHS data when a capacity of 500 was used. The NHS data for 'average number of patients delayed in hospital' and 'average delayed bed days for patients waiting 7+ days' was closely matched by the simulation output, and the metrics 'average delayed bed days for patients waiting 14+ days' and 'average delayed bed days for patients waiting 21+ days' were underestimated by the model. The underestimation of these metrics is due to the current modelling assumption of homogeneity in patient characteristics. Future work will consider introducing variables that affect a patient's discharge from hospital e.g., medical complications and conditions which make it difficult to find a care placement.

Table 2: Baseline model output with varied D2A Home Capacity compared with NHS England (2022). In each case the point estimated is reported with 95% Confidence Intervals in brackets.

| Experiment | Average no. patients delayed in hospital | Average delayed bed days for patients waiting 7+ days | Average delayed bed days for patients waiting 14+ days | Average delayed bed days for patients waiting 21+ days |
|---|---|---|---|---|
| NHS Data | 208 | 2543 | 2357 | 2089 |
| 350 D2A Home | 320 (315,324) | 2837 (2790,2884) | 2086 (2046,2125) | 1479 (1441,1517) |
| 400 D2A Home | 273 (269,276) | 2751 (2682,2821) | 2090 (2025,2154) | 1516 (1456,1575) |
| 450 D2A Home | 230 (227,233) | 2605 (2530,2680) | 2036 (1963,2109) | 1498 (1430,1566) |
| 500 D2A Home | 205 (203,207) | 2493 (2417,2570) | 1977 (1908,2047) | 1466 (1406,1526) |
| 550 D2A Home | 202 (199,205) | 2514 (2442,2586) | 2000 (1931,2068) | 1468 (1422,1551) |
| 650 D2A Home | 202 (199,205) | 2514 (2442,2586) | 2000 (1931,2068) | 1468 (1422,1551) |

### 4.2 Sensitivity Analysis

The D2A Home capacity was therefore fixed at 500 and used for the remaining experiments. Sensitivity analysis was performed on the probability of acceptance at a nursing home (per day). The baseline assumption is an acceptance probability of 1/7 (where patients wait an expected time of 7 days). Table 3 shows the model output when this parameter is varied between 1/3 and 1/10. The model behaves as expected, where a lower acceptance probability corresponds to higher average numbers of patients delayed in hospital and higher average delayed bed days across all categories. A similar sensitivity analysis is presented in Table 4 for the probability of acceptance for care at home, where the baseline assumption is 1/3 and the parameter is varied from 1/2 to 1/5. Similarly, a decrease in this acceptance probability corresponds to higher numbers of delayed patients and delayed bed days. The results in Tables 3 and 4 demonstrate that the baseline acceptance probabilities of 1/7 for nursing home and 1/3 for care at home provide the best match to the data.

Table 3: Sensitivity analysis for Nursing home acceptance probability, with care at home acceptance probability fixed as 1/3 and D2A Home capacity set as 500. In each case the point estimated is reported with 95% Confidence Intervals in brackets.

| Nursing home acceptance probability | Average no. patients delayed in hospital | Average delayed bed days for patients waiting 7+ days | Average delayed bed days for patients waiting 14+ days | Average delayed bed days for patients waiting 21+ days |
|---|---|---|---|---|
| 1/5 | 119 (118,121) | 923 (897,949) | 609 (585,632) | 368 (349,386) |
| 1/6 | 162 (160,164) | 1624 (1588,1660) | 1200 (1164,1236) | 822 (784,859) |
| 1/7 | 205 (203,207) | 2493 (2417,2570) | 1977 (1908,2047) | 1466 (1406,1526) |
| 1/8 | 246 (243,250) | 3475 (3386,3564) | 2872 (2787,2958) | 2226 (2142,2310) |
| 1/9 | 288 (284,291) | 4688 (4595,4780) | 4019 (3928,4110) | 3265 (3187,3343) |
| 1/10 | 329 (326,332) | 6063 (5925,6200) | 5340 (5205,5474) | 4488 (4359,4616) |

Table 4: Sensitivity analysis for care at home acceptance probability, with nursing home acceptance probability fixed as 1/7 and D2A Home capacity set as 500. In each case the point estimated is reported with 95% Confidence Intervals in brackets.

| Care at home acceptance probability | Average no. patients waiting in hospital | Average delayed bed days for patients waiting 7+ days | Average delayed bed days for patients waiting 14+ days | Average delayed bed days for patients waiting 21+ days |
|---|---|---|---|---|
| 1/2 | 202 (199,204) | 2514 (2442,2586) | 2000 (1931,2068) | 1486 (1422,1551) |
| 1/3 | 205 (203,207) | 2493 (2417,2570) | 1977 (1908,2047) | 1466 (1406,1526) |
| 1/4 | 356 (352,360) | 3376 (3316,3436) | 2477 (2419,2534) | 1722 (1668,1776) |
| 1/5 | 539 (535,543) | 5166 (5095,5237) | 3757 (3694,3821) | 2544 (2489,2599) |

### 4.3 Scenario Analysis

Table 5: Scenario analysis for the capacity of D2A Inpatient resource, where D2A Home capacity is set at 500 and acceptance probabilities 1/7 and 1/3 for nursing home and care at home respectively. In each case the point estimated is reported with 95% Confidence Intervals in brackets.

| D2A Inpatient Capacity | Average no. patients waiting in hospital | Average delayed bed days for patients waiting 7+ days | Average delayed bed days for patients waiting 14+ days | Average delayed bed days for patients waiting 21+ days |
|---|---|---|---|---|
| 75 (baseline) | 205 (203,207) | 2493 (2417,2570) | 1977 (1908,2047) | 1466 (1406,1526) |
| 85 | 195 (192,197) | 2419 (2393,2444) | 1927 (1909,1945) | 1438 (1424,1453) |
| 95 | 185 (182,187) | 2237 (2170,2304) | 1755 (1686,1823) | 1289 (1226,1343) |

Scenario analysis was performed to investigate the effect of increasing the number of available D2A Inpatient resources from 75 to 85 and 95. Table 5 shows a reduction of approximately 10 in the average number of patients waiting in hospital for an increase of 10 D2A Inpatient beds. There is also a marked reduction in the number of delayed bed days for patients in each of the 7+, 14+ and 21+ categories.

## 5 CONCLUSION

This paper presented a conceptual model and discrete event simulation of the discharge process from inpatient hospitals in the UK. The model specifically considered delayed discharge at the University Hospital Southampton (UHS). Although this is only preliminary work, the results showed a close match to the most recent data from UHS, where 208 patients were delayed in hospital and there were 2543 excess bed days for patients waiting more than 7 days. The number of excess bed days for patients waiting over 14 and 21 days was underestimated by the model. Sensitivity analysis showed that decreasing the probability of acceptance to a nursing home and care at home led to an increased number of patients delayed in hospital and an increase in excess bed days. Scenario analysis showed that increasing the capacity of the inpatient discharge to assess process could lead to a reduction in the number of patients delayed in hospital and associated excess bed days.

Future work will consider how to improve the model so that the output better represents the distribution of excess bed days. One of the key parameters in the simulation model is the probability of acceptance in care, which we estimate differently for nursing home care and care at home but do not vary between patients. In reality the probability of a patient being accepted into care varies significantly between different patient types. For example, Flinders and Scobie (2022) suggests that patients who have an initial hospital stay of 3 weeks or more are more likely to suffer long delays to discharge. These patients tend to be elderly and frail and have more complex needs, hence requiring a higher level of care. Taking into account the differences in probability of acceptance into care between different patient groups rather than assuming the population is homogeneous will improve the ability of the model to reproduce observed behaviour and will also help to better understand the relative benefits of increasing provision for hard-to-place patients versus improving the system more generally. Future development of the model will also consider adding variation in the probability of acceptance to community care facilities by day of the week and obtaining more data to better inform estimates of the duration of time patients spend in D2A processes. The model will be translated into SimPy to make it open source and to give more control over running experiments.

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