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Original Study

Avoiding Hospital Admissions and Delayed Transfers of Care by Improved Access to Intermediate Care: A Simulation Study

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ABSTRACT

Objective: The current waiting times for intermediate care in the Netherlands prohibit timely access, leading to unwanted and costly hospital admissions. We propose alternative policies for improvement of intermediate care and estimate the effects on the waiting times, hospitalization, and the number of patient replacements.
Design: Simulation study.
Setting and Participants: For our case study, data were used of older adults who received intermediate care in Amsterdam, the Netherlands, in 2019. For this target group, in- and outflows and patient characteristics were identified.
Methods: A process map of the main pathways into and out of the intermediate care was obtained and a discrete event simulation (DES) was built. We demonstrate the use of our DES for intermediate care by evaluating possible policy changes for a real-life case study in Amsterdam.
Results: By means of a sensitivity analysis with the DES, we show that in Amsterdam the waiting times are not a result of a lack in bed capacity but are due to an inefficient triage and application process. Older adults have to wait a median of 1.8 days for admission, leading to hospitalization. If the application process becomes more efficient and evening and weekend admissions are allowed, we find that unwanted hospitalization can be decreased substantially.
Conclusion and Implications: In this study, a simulation model is developed for intermediate care that can serve as a basis for policy decisions. Our case study shows that the waiting times for health care facilities are not always solved by increasing bed capacity. This underlines the necessity for a data-driven approach to identify logistic bottlenecks and find the best ways to solve them.

Older adults admitted to the hospital are at risk of adverse health outcomes, such as infections, delirium, falls, and even death.[1–3] Moreover, prolonged hospital stays caused by delayed transfers of care often lead to adverse events[4,5] and high costs.[6] In response to this, during the last decade many governments implemented intermediate care with the aim to avoid hospital admissions and to support older adults in their recovery after hospital admission. Currently, inadequate access to intermediate care hinders the potential benefits of the facilities to the care system.[7] If we know what intermediate care capacity is needed and which policies perform best, we can prevent hospital admissions and the consequent high costs.

It is, however, not trivial to determine which policies are the most effective for the improvement of intermediate care. A solid method that can be used to predict outcomes of policy changes is discrete event simulation (DES). With this approach, process characteristics are identified and modeled as a sequence of events in time. DES is applied to many health care settings, for example, emergency departments[8] or intensive care.[9] However, little research has been conducted on simulation of intermediate care facilities. To our knowledge, no study models intermediate care as a midchain care form in which avoidable hospital admissions are considered as well, which is a necessity for determining the systemwide policy effects.

In this study, we develop a DES model that can be used to evaluate which policy change is likely to be the most effective in the prevention

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of bed blocking in hospitals and intermediate care. Using the model, we run a case study for the city of Amsterdam, the Netherlands. In this study, we address the following research question: How can the organization of intermediate care be adjusted such that the number of hospital admissions, delayed transfers of care, and patient transitions are reduced?

Method

Background

Intermediate care is defined by an international panel as a broad range of time-limited services, from crisis response to support for several weeks or months, that aim to ensure continuity and quality of care and promote recovery at the interface between hospital and home, care home, primary care, and community services.[10] In the Netherlands, the government implemented Short-Term Residential Care (STRC) in 2015 as part of major health care reforms because of rising expenses.[11] STRC is bed-based care for general health problems that do not require admission to the hospital, but also cannot be treated at home.[12] The goal of STRC is to enable older adults to return home and live independently in the community.

In the Netherlands, 3 types of STRC are provided: low-complexity, high-complexity, and hospice care.[13] Low-complexity care only provides care in activities of daily living (ADL) and the general practitioner is the responsible physician. In addition to ADL care, STRC high-complexity provides 1.5 hours of treatment per week such as physical therapy, medical diagnostics, or occupational therapy. STRC hospice care provides care in the last 3 months of life.

Flow Diagram

The admission control for all STRC locations in the Netherlands is regionally centralized. For that reason, we can use one model at the aggregated level of a complete region. Figure 1 shows a flow diagram of the patient journeys through STRC.

In Figure 1, we see that admission to STRC occurs via 2 waiting lists. The first waiting list (W1) is for admissions from the home situation. The patient is referred by the general practitioner (GP) or emergency department (ED) and is not in need of hospital-level care. The second waiting list (W2) is for patients residing in the hospital needing extra time to recover in intermediate care. The patients at W1 have priority over the patients at W2, because W1 patients often have a pressing need for care that cannot be provided at home. Moreover, patients from the ED need to be admitted to STRC within the same day, because otherwise a hospital admission is required. After the stay in STRC, the patient is discharged to home, is discharged to another care provider, or has died.

Furthermore, because of staff shortages, STRC admissions in the evenings or weekends are often not possible. For the weekends, we have admission data that confirms this (see Supplementary Figure 1). Finally, a transfer time is needed to do the administration and transfer of an older adult to the STRC location. By expert discussion, this transfer time was estimated to be on average 1.5 days.

Data Collection

Various data sources containing STRC admissions were collected. In Amsterdam, almost all STRC care is high-complexity, which is therefore the focus of this research. Henceforth, the term STRC will be used for our focus care type: high-complexity STRC. We only used data from 2019, such that COVID-19 did not affect the patient flows. The following data sources were obtained.

- *Nonpublic microdata of Statistics Netherlands.* This data source contained health care expenses at the individual level from which bed occupation, admissions, lengths of stay, and discharge destinations could be determined.
- *Hospital STRC.* These data were from an STRC that is located in a hospital. This STRC functions as a real-life case study for what happens if the admission to STRC is not hindered by logistic inefficiencies.
- *Data from the centralized admission portal.* This data source provided us with the number of STRC beds in Amsterdam and the GP waiting times for STRC.

We needed to receive permission to make use of the microdata database, and these data could only be accessed via a secured portal. Both other data sets were anonymized and did not contain sensitive patient data. Concerning the ethics, this study does not fall under the scope of the Medical Research Subjects Act.

Alternative Policy Scenarios

Current organizational problems of the STRC were collected during a previous qualitative study in 2018.[12] In addition, we spoke to employees of the centralized admission portal and health care organizations facilitating STRC. The problems that were deemed most urgent were lack of possibilities to admit patients during the evening and

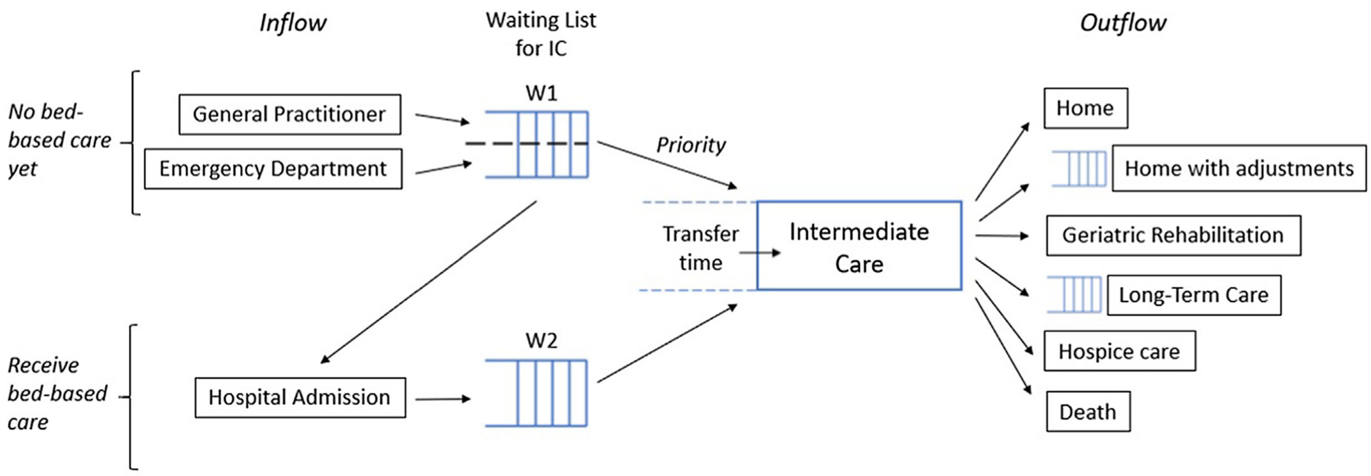

Fig. 1. Current practice flow diagram STRC.

weekends, missing information during the admission process, shortage of time and money during an admission to treat patients, and lacking adjustments at the home of the older adult admitted to STRC. These problems were translated into possible process improvements, which are evaluated in the simulation as scenarios. We distinguish the alternatives (1) in front, (2) during admission, and (3) at the back. The following scenarios were obtained.

Alternatives in Front

Admission turns

The proposed alternative is to compensate STRC locations for keeping beds available in the evening for admission by turn. This means that every other evening, night, or weekend day a specific location is responsible for admissions from the GP, ED, or hospital. We model this by allowing 24/7 STRC admissions and a transfer time of 4 hours.

Triage ward

Another scenario is to set up a triage ward, as illustrated in Figure 2. The triage ward is intended for older patients for which it is unclear what type of care is needed. The maximum length of stay in the triage ward is 14 days, after which patients are discharged to STRC or another destination. We model the Triage Ward by allowing 24/7 STRC admissions and a transfer time from the hospital to the Triage Ward of 4 hours. The average transfer time from the Triage Ward to the STRC remains 1.5 days. For a flow diagram of this scenario, see Supplementary Figure 2.

Alternative During Admission

Higher tariff

The current tariff that STRC organizations receive from health insurers is to provide up to 1.5 hours of diagnostics and treatment per week, which is rather low compared to the high intensity of needed care.[10] The proposed alternative is to increase the tariff, such that more hours of diagnostics and treatment are possible and multiple treatment types can be provided in parallel. As a result, the length of stay (LoS) becomes shorter.

Alternative at the Back

Reduce bed-blocking

Patient discharges can be delayed because of the lack of timely home adjustments required for the patient to return home. Such home adjustments are for example a stairlift or supporting handles in the shower. In addition, waiting lines for LTC can be shortened by increased facility capacity or by improved waiting-line management.[14] We model the effect of this policy by a reduced length of stay (LoS) for the patients that require home adjustments or need long-term care.

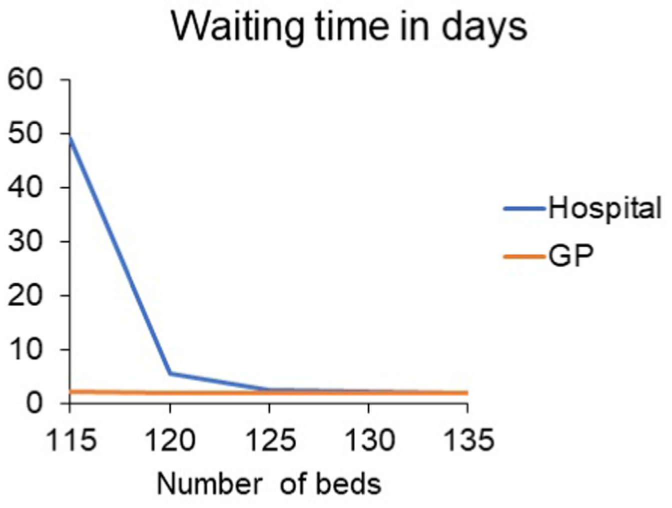

Fig. 2. Expected waiting time for STRC for different number of beds.

Simulation

After the process map was obtained and the data were collected, the DES model was developed. DES is a mathematical technique in which process characteristics are identified and modeled as a sequence of events in time. Examples of events are the arrival of a new patient and a patient's discharge. Using the DES, the impact of alternative policies can be evaluated. More information about the DES method can be found in the literature.[13]

Using the data, we checked which probability distributions could be used best for modeling the arrivals and lengths of stay. The arrival process is modeled as a Poisson process in which we included some time restrictions. For the ED arrivals, we use evidence from the literature that most ED patients arrive between 8 AM and 12 PM.[15] All lengths of stay are modeled as exponential or gamma distributions. The statistical tests for these assumptions are presented in Supplementary Material. Finally, a model validation was performed to check if our DES represents the actual situation. It was found that indeed our simulation results matched the real data for 2 evaluated outcome measures: occupied bed distribution and GP waiting times. The results of this validation can be found in Supplementary Material.

The outcome measures that we aim to evaluate in the DES are presented and elucidated in Table 1.

Results

Flow Data

It should be noted that with the data, only *realized* care journeys could be determined that might differ from the *intended* ones because of logistic bottlenecks. For STRC, the inflows might be affected by hospital admissions of patients for which timely STRC admission was

Table 1
Description of Outcome Measures

Outcome Measure	Description
Waiting time hospital	The average time between a planned hospital discharge and placement in STRC
Waiting time GP	The average time between STRC application by the GP and placement in STRC
Percentage of nonurgent (N-U) patients placed within 3 d	The percentage of older adults that are nonurgent, ie, patients referred by the GP or from the hospital, for which the time between application and placement in STRC is less than 3 d
Percentage of patients presented at the ED that need a hospital admission	Percentage of older adults at the ED for which no STRC admission was possible within the same day, for which a hospital admission was necessary
Number of patient replacements	The average number of older adult replacements, where we count admission to STRC, hospital admission from the ED, admission to the Triage Ward, and STRC discharge as replacements
Number of patients delayed per day	The average number of older adults per day that are waiting in a hospital bed for an STRC bed

Table 2
Flow Data

Parameter	Mean Value
Inflow requests, no. of older adults per week	
General practitioner	9.4
Emergency department	5.8
Hospital admission	6.6
Outflow fraction, %	
Home/other	57.8
Home with adjustments	10.7
Long-term care	19.8
Geriatric rehabilitation	3.4
Hospice care	2.3
Death	6.0
Average length of stay, d	
STRC → Home/other	31.1
STRC → Home with adjustments	43.9
STRC → Long-term care	47.8
STRC → Geriatric rehabilitation	29.8
STRC → Hospice care	22.9
STRC → Death	22.9
Hospital admission	5.2
Number of beds in STRC	128

not possible. We find in the data of the Hospital STRC in 2019 that 117 patients were transferred from the ED, and 131 patients were admitted after a hospital admission. This implies that among the patients that arrived via a care form, the inflow of older adults from the ED was 47% and from a hospital admission was 53%. Moreover, from the microdata of Statistics Netherlands we also obtain inflow percentages for Amsterdam, of which 25% of the older adults transfer from the ED and 75% from a hospital admission. This large deviation of inflow percentages from the Hospital STRC might indicate that about half of the current ED visits leads to a redundant hospital admission.

The inflow values of the ED and Hospital Admission were identified by the microdata source, which led to a total of 12.4 older adults' admissions per week. These were distributed according to the 47:53 ratio, which led to 5.8 and 6.6 admissions per week. The results of the data analysis are provided in Table 2.

Table 2 shows that the lengths of stay for home care with adjustments and LTC are the longest. The expected reason for this is that patients have to wait before these services are available before they can be transferred. However, it can also be the case that these patients have more complex problems, which results in a longer rehabilitation.

Number of Beds

Because we have validated the current practice model, we can now see the results of other scenarios. First, we check if the waiting times are the result of a lack in number of beds. For that purpose, we run the current practice simulation with varying number of beds, see Figure 1.

Figure 1 shows that, most surprisingly, the current number of beds (128) is not the cause of the waiting times, because increasing the number of beds does not lead to a significant reduction. Moreover, it becomes clear that the patients from the GP have priority over patients from the hospital. The waiting time of 1.8 days is thus the result of the transfer time (which is on average 1.5 days) and the result of the lack of admission possibilities outside office hours. Alternative policies might reduce the waiting times, which we explore in the next step.

Alternative Policies

The current practice and alternative policies were simulated for varying numbers of beds, which resulted in the output provided in Table 3. CIs of simulation outputs provide the statistical bounds on the means.[16] Our simulations were run until the width of the 95% CIs on the waiting time for the hospital was less than 0.1 day. Therefore, the results were presented as point estimates without the intervals. The descriptions of the outcome measures can be found in Table 1.

We see that in the current practice scenario, the fraction of ED visits leading to a hospital admission is 51%, which is in line with the expectation of the current process.

We also see that only with a policy aiming at the admission access (ie, Admission Turns and Triage Ward), the waiting times can be reduced. This is in line with our earlier observation that the waiting times are a result of an inefficient admission process. Moreover, for these policies, the hospital admissions from the ED are reduced. We see that the Triage Ward performs equal to all outcome measures compared to the Admission Turns policy, except for the number of patient replacements which increases from 2.0 to 2.7.

With the Higher Tariff scenario, we have that if the lengths of stay can be reduced by 30%, the number of beds can be reduced from 128 to 100 without an increase in waiting time. The bed-blocking scenario also leads to possible reductions in number of beds. The gain is the largest when reducing the length of stay for the patients who transfer to long-term care, because these current lengths of stay are longer and the fraction of patients is the highest.

Table 3
Simulation Results: Comparison Between Current Practice and Alternative Scenarios

Scenario	Number of Beds	Waiting Time for Hospital, d	Waiting Time for GP, d	% N-U Placed <3 d	% ED → Hospital Admission	No. of Replacements	No. of Patients Delayed per Day
Current practice	128	2.4	1.8	79	51	2.1	3.3
Admission turns	128	0.2	0.1	100	3	2.0	0.2
	115	3.8	0.3	88	33	2.1	4.6
Triage ward	80, TW = 48	0.2	0.1	100	3	2.7	0.2
	80, TW = 40	6.8	0.6	85	30	2.8	8.1
Higher tariff							
LoS reduction of 30%	128	1.8	1.8	82	46	2.1	2.4
LoS reduction of 30%	100	1.9	1.8	82	48	2.1	2.5
LoS reduction of 20%	100	3.3	1.9	75	58	2.2	4.7
Reduce bed blocking							
HWA LoS reduction of 30%	128	1.9	1.8	82	48	2.1	2.6
LTC LoS reduction of 30%	128	1.8	1.8	82	47	2.1	2.4
LTC LoS reduction of 30%	110	8.0	2.0	66	67	2.2	12.0
Combinations							
AT + HT (LoS reduction of 30%)	100	1.1	1.1	100	0	2.0	0.1
AT + HT (LoS reduction of 30%)	80	6.3	0.4	83	45	2.1	8.2

AT, admission turns; HWA, home with adjustments; HT, higher tariff; LTC, long-term care.

Finally, some combinations of alternative policies were run. We see that if both the Admission Turns and Higher Tariff policies are implemented, the number of STRC beds can be reduced to 100 whereas also the waiting times are reduced, the number of hospital admissions is reduced and the number of patients in the wrong beds are almost zero.

Discussion

In this research, a simulation study was performed to evaluate the effects of alternative policies to improve intermediate care. For a case study of the city of Amsterdam, the Netherlands, it was found that the current waiting times for the intermediate care facilities are not due to a shortage in the number of beds, but are the result of an inefficient admission process. We show that if the organizations make the application process more efficient and extend the office hours' time frame with an evening and weekend admission policy, the number of unwanted hospital admissions prior to intermediate care can be decreased from approximately 51% to 3%.

In addition, if a higher tariff is introduced that reduces the lengths of stay by 30%, the number of beds can be decreased by 22% without an increase in waiting times. A reduced length of stay can also be obtained by cutting down waiting times for follow-up care, but because this concerns only a fraction of the patient outflow, the effects are smaller. The Triage Ward policy leads to the unwanted consequence that a high number of patient replacements were performed. This policy should therefore only be implemented if it supports the care process in other aspects such as succeeding in allocating patients directly to the right care form. Finally, combining the right policies leads to the largest gain in reduced waiting times and bed capacity.

To our knowledge, our approach to model the intermediate care facilities as a midchain care form in the health care system in which we also consider the admission policies is unique. In an earlier intermediate care simulation study, no admission policy is mentioned and it is assumed that the older adults wait until their best-fitted care form is available, which might be less realistic in acute situations.[17] In addition, a literature review of modeling studies for intermediate care showed that little modeling studies focus on outflow to community health services, comparable to intermediate care, and do not often focus on the connection to the use of acute care.[18] Finally, one study did construct the care pathway of intermediate care, but the researchers were not able to test alternative scenarios.[19]

Besides the possible improvements in patient satisfaction and health outcomes, we also might save costs if the process flow is improved. In particular, the average tariff for 3 days' hospital admission due to older adults' problems is €900 per day.[20] Multiplied by the number of hospital-days saved per day for the Admission Turns policy (3.2 days saved), an estimated €2880 per day can be saved because of hospital avoidance. The intermediate care literature is primary focused on the cost-effectiveness of the supported discharge goal of intermediate care and not on admission avoidance.[21] This article thus also contributes in that aspect. Moreover, it was found that admission avoidance in particular leads to cost savings,[21] which is in line with this study as well.

Our study has several strengths and limitations. A valuable contribution is that we consider the whole chain of admission and discharge in which intermediate care is involved. Furthermore, our study focuses on cost-effectiveness as well as on patient relevant outcomes such as number of transfers. A limitation of our study is that we could not include process features in our simulation, for which we lacked data. First, a small fraction of the intermediate care beds is dedicated to observation of older adults who had a delirium and are recovering from this delirium. However, we do not have data about the patient arrivals for these specific beds, which are therefore not considered. Second, acute patients from the ED can be surpassed by (not acute) hospital patients, because the hospital patients already claimed a bed in the intermediate care facility. As we do not have information about the number of cases in which this happens, this feature was also left out.

Conclusions and Implications

In this study, we found that simulation is an effective tool for modeling intermediate care facilities and determining policies for improvement. In our case study, we show that with the right policies, less beds (and hence personnel) are needed for intermediate care in Amsterdam. The improved access to these facilities implies that more hospital admissions can be avoided and bed blocking in the hospital can be reduced. Moreover, the newly available beds can be dedicated to other care forms for which a shortage exists, such as long-term care. Hence, an efficiency improvement of one pivotal care facility leads to an improvement of the older adults' care system as a whole.

Currently, decisions on health care interventions and capacities are often made without sound quantitative insights into the effects of the decisions. This research shows the importance of a simulation approach for improvement of the care domain of older adults. This novel strategy can prevent high costs and effort put into multiple pilot studies of which it is unclear whether the intended outcomes will be obtained. For example, in Amsterdam a pilot study could have been set up to reduce the length of stay of the intermediate care facilities, which would not have led to a decrease in waiting times. Therefore, a data-driven approach is essential to identify problems' true causes and appropriate solutions, which results in increased cost-effectiveness and patient satisfaction.

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Supplementary Material

Distribution Tests

To perform the simulation, we need to identify the probability distributions underlying the arrival processes and lengths of stay.

Arrivals

For the distribution of the arrivals, we plotted the weekly number of arrivals to intermediate care and the fitted Poisson distribution, see Supplementary Figure 3.

Moreover, a chi-square test indicated that the number of arrivals per week can be according to a Poisson distribution $\chi^2(\mathrm{df} = 15, \mathrm{N} = 52) = 11.0$, $P > .05$.

Length of Stay

The lengths of stay were identified per outflow type and plotted together with the best-fitted probability distribution (see Supplementary Figure 4).

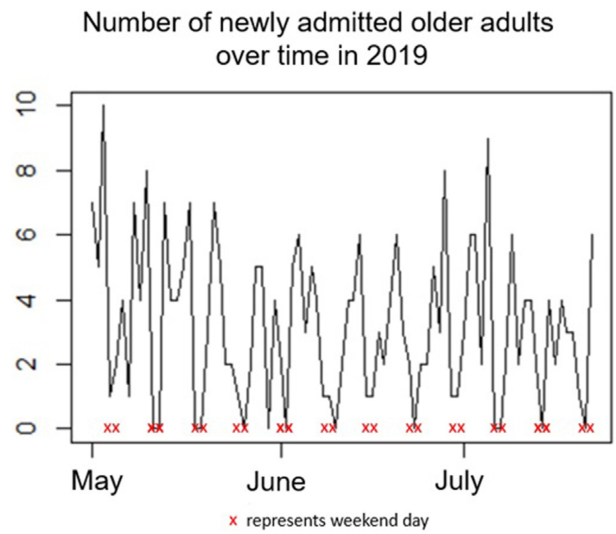
We tested statistically whether the data could be the realization of the underlying probability distributions. For this, we used the Kolmogorov-Smirnov tests, with the null hypothesis that the empirical distributions are sample realizations of the proposed distributions. For all distributions, the null hypotheses were not rejected at a 95% confidence level ($P > .05$).

Model Validation

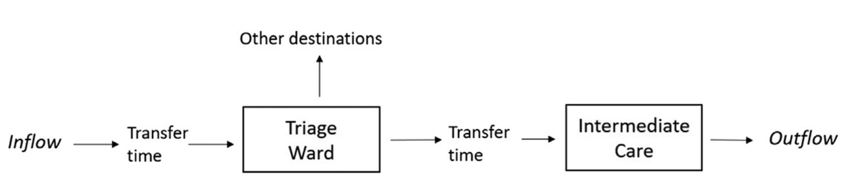
We were able to validate our model, that is, to check if our current practice simulation represents the real situation. We do this by comparing the distribution of occupied beds resulting from our simulation with real data based on nonpublic data from Statistics Netherlands.

We see in Figure 5 that the simulated occupied bed distribution is quite similar to the real data. The mean occupancy is 84% (simulated) vs 85% (real data). In the Supplementary Figure 5, we also see that the real data are slightly more concentrated around the mean than the simulated data.

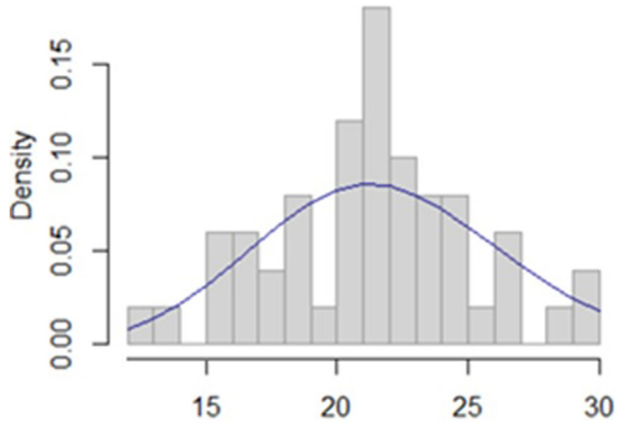
In Supplementary Figure 6, we see boxplots of the simulated waiting times until placement in STRC next to the real waiting times data. We see that the boxplots are rather similar except for the lowest quarter. An explanation for this is that the waiting times in the real data are only on day basis and not per hour, which leads to 25% of the waiting times to be exactly zero.



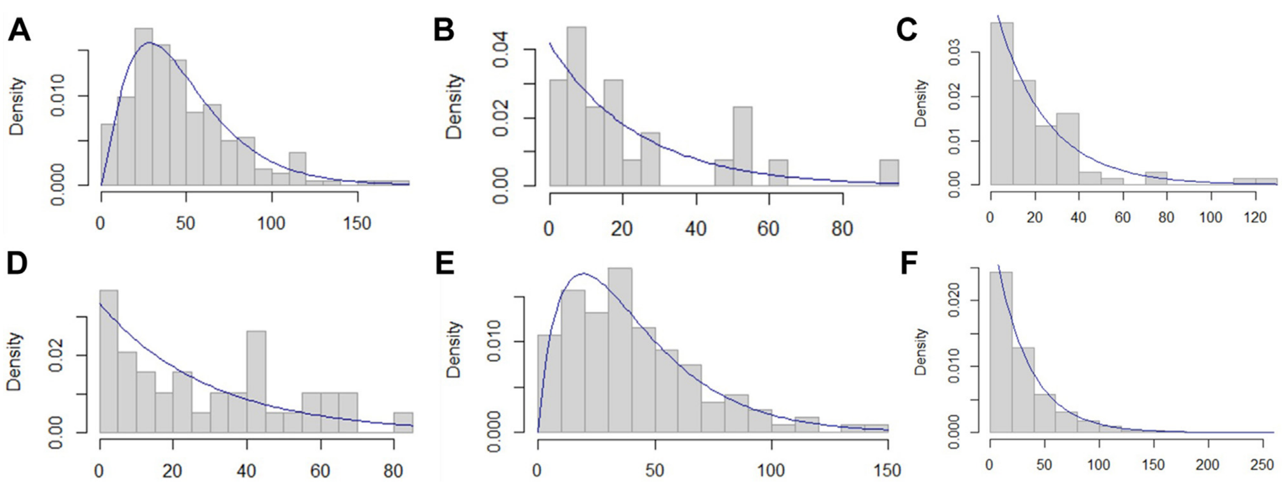
Supplementary Fig. 1. Number of STRC admissions showing a decrease during weekend days.



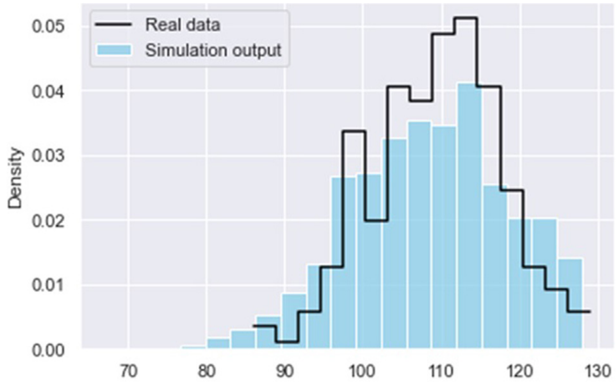
Supplementary Fig. 2. Scenario Triage Ward.



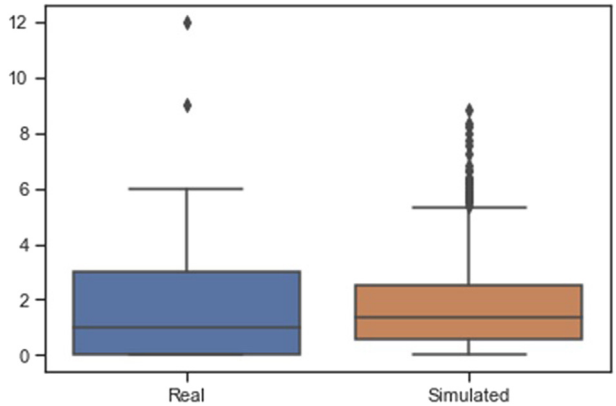
Supplementary Fig. 3. Density plot with weekly arrivals (bars) and fitted Poisson distribution (line).



Supplementary Fig. 4. Density plot per outflow type with lengths of stay (bars) and best fitted distribution (line) .a. Long-term care (gamma) b. Hospice care (exponential) .c. Death (exponential). d. Geriatric Rehabilitation (exponential). e. Home with adjustments (gamma) f. Home (exponential).



Supplementary Fig. 5. Occupied bed distribution.



Supplementary Fig. 6. Waiting times from GP.