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ORIGINAL RESEARCH

# New bed configurations and discharge timing policies: A hospital-wide simulation

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## Abstract

***Objective***: Optimising patient flow is becoming an increasingly critical issue as patient demand fluctuates in healthcare systems with finite capacity. Simulation provides a powerful tool to fine-tune policies and investigate their impact before any costly intervention.

***Methods***: A hospital-wide discrete event simulation is developed to model incoming flow from ED and elective units in a busy metropolitan hospital. The impacts of two different policies are investigated using this simulation model: (i) varying inpatient bed configurations and a load sharing strategy among a cluster of wards within a medical department and (ii) early discharge strategies on inpatient bed access. Several clinically relevant bed configurations and early discharge scenarios are defined and their impact on key performance metrics are quantified.

***Results***: Sharing beds between wards reduced the average and total ED length of stay (LOS) by 21% compared to having patients queue for individual wards. The current baseline performance level could be maintained by using fewer beds when the load sharing approach was imposed. Earlier discharge of inpatients resulted in reducing average patient ED LOS by approximately 16% and average patient waiting time by 75%. Specific time-based discharge targets led to greater improvements in flow compared to blanket approaches of discharging all patients 1 or 2 hours earlier.

***Conclusions***: ED access performance for admitted patients can be improved by modifying downstream capacity or inpatient discharge times. The simulation model was able to quantify the potential impacts of such policies on patient flow and to provide insights for future strategic planning.

**Key words:** *decision making, decision support systems, discrete-event simulation, resource management, strategic planning.*

## Key findings

- The impacts of two interventions or 'levers' to improve patient flow through the ED were quantified via a hospital-wide simulation: varying inpatient bed configurations and inpatient discharge time.
- Sharing beds between inpatient wards reduces average and total ED length of stay by 21% or allows baseline performance to be maintained using fewer beds.
- Earlier discharge of inpatients results in reducing average patient ED length of stay by approximately 16%. Specific time-based discharge targets lead to greater improvements in flow compared to blanket approaches of discharging all patients 1 or 2 hours earlier.

## Introduction

Hospitals and health services are facing increasing demand that has led to overcrowded EDs and increases in the time patients spend waiting to access treatment.[1] There are pressures facing all hospitals to match this demand with available beds in order to get unwell patients into hospital beds in a timely manner. Optimising patient flow is becoming increasingly critical in a health system with finite capacity to deal with this rapid growth. At the same time, it is important to maintain health service performance against measures such as ED wait times and surgery targets. Although trials of strategic interventions to cope with hospital overcrowding are costly and sometimes impractical and risky, computer simulation provides a

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powerful tool to quantify and investigate the potential impact of such interventions. With the availability of electronic health records, various computational simulation and optimisation approaches have been devised in order to provide insights towards optimising patient flow management.[2–5]

Discrete event simulation (DES), agent-based simulation, system dynamics and hybrid models based on these are common simulation approaches in various domains.[6–16] In the healthcare domain, DES is among the most commonly used method of simulation,[4,11,17–22] where a system is modelled with a number of resources (with defined capacities), queues, and a series of events.[23] The DES approach offers better representations than other afore-mentioned individual techniques to model complex systems involving individual movements between resources and queues.[7] Carter *et al.* proposed a DES model for endoscopy waiting list for two metropolitan health services.[17] Their simulation estimated 46% and 97% increases in long wait patients over the course of 5 years in the two healthcare services if they continued functioning with their current capacities. A patient flow simulation for patient with acute coronary syndrome was proposed by Kovalchuk *et al.* where different clinical patient pathways were identified and used as input information to a DES simulation model.[19] They tested different surgery room availability and flow rates to identify the top-three clinical pathways to better cope with the demand. They also showed that increasing surgery rooms from three to four may significantly decrease the chance of patients waiting in a queue.

Qin *et al.* proposed a DES-based simulation model for testing various discharge scenarios that was based on a previously developed approach.[24] Nine discharge scenarios were considered that focused on testing four main concepts: (i) 24 h/day discharge, (ii) instantaneous discharge, (iii) early discharge of long-stay patients and (iv) reducing length of stay (LOS) by half a day for patients with LOS of more than 1 and 2 days. Although found to be operationally impossible, they showed that discharging all patients with LOS of greater than 21 days could result in an ideal state for the hospital's occupancy level.

In the present study, we developed a DES-based approach to present a hospital-wide simulation of patient flow to quantify the impacts of various operationally plausible policies to improve flow metrics. Several bed configurations and early discharge timing scenarios were identified through discussions with hospital staff. The developed and validated simulation model was then used to quantify their impact on key patient flow performance metrics. The output of the model was compared to a baseline setting to scale the impacts and to inform future patient flow improvements.

## Methods

### *Data*

Data for the present study was sourced from the Integrated Electronic Medical Record (ieMR) Clinical Data Repository that provides real-time patient information. The data included movements for ED and elective patients from the point of admission to discharge from hospital between 1 July 2018 and 31 December 2019 at one of the Queensland's major metropolitan hospitals. Operational information related to inpatient ward and bed configurations, available beds and ward closures, and process and workflow changes during the analysis period was also obtained from the hospital.

Data was obtained for 27 participating wards with available capacity throughout the study period. Spaces without defined capacity, such as treatment bays, operation suites, transit, and day therapy wards were grouped and classified as 'OTHER' wards. These 'OTHER' wards do not cause any patient flow bottleneck in our simulation modelling. All types of encounters were considered in our hospital-wide simulation model: ED-only encounters ($n$ = 71 740), ED to Inpatient (ED2IP) encounters ($n$ = 69 805) and Elective encounters ($n$ = 54 032). Detailed definitions can be found in Appendix S1.

### *Bed configuration scenarios*

In many hospitals, beds are statically assigned to specialty units and wards following historical practices. Such a static bed allocation is not necessarily an optimal strategy with regards to patient flow performance. A simulation model can provide insights about potential impact of strategies towards optimising bed managements. Our approach focused on defining scenarios for simulation in collaboration with senior hospital administrators, ensuring that models were based on practical strategies that could be translated to practice if proven to be effective through the modelling exercise. The developed scenarios adopted a clustering approach to capacity management instead of changing the ward-level routine. Working with operational and clinical experts, we identified wards that can be potentially grouped together based on both their clinical/treatment purpose and location within the hospital. This allowed patients to be allocated another ward within the same cluster when the initial target ward was overloaded (i.e. no available bed to admit waiting patients) and the other ward had capacity to admit waiting patients in the queue. This exercise was undertaken with the aim to reduce waiting times, especially for patients waiting to be admitted to their first inpatient ward after ED discharge. As suggested by the hospital staff, the wards were grouped according to their treatment type:

- Cluster 1 (Medical wards): 3A, 3B, 3C, AMU, MAPU, 3CCARD
- Cluster 2 (Surgical wards): 2H, 2I, SURGSS
- Cluster 3 (Mental Health wards): 2B, 2C, 2J, 2K, 2L, 2A
- Cluster 4 (Adult ED Short Stay wards): EDSSW, EDCDU
- Cluster 5 (Children wards): CIU, EDSSC

More details on patient journeys and common clinical pathways at the study hospital is provided in Appendix S1.

**TABLE 1.** *Summary of early discharging scenarios*

| Scenario | Discharge target |
|---|---|
| Scenario 1 | 50% by 10.00 hours, 80% by 12.00 hours, 100% by 14.00 hours |
| Scenario 2 | 35% by 11.00 hours, 70% by 14.00 hours, 100% by 17.00 hours |
| Scenario 3 | 50% by 11.00 hours, 70% by 14.00 hours, 100% by 17.00 hours |
| Scenario 4 | 80% by 11.00 hours |
| Scenario 5 | 40% by 10.00 hours, 70% by 14.00 hours, 90% by 17.00 hours, 100% by 22.00 hours |
| Scenario 6 | Discharge all patients 1 h earlier |
| Scenario 7 | Discharge all patients 2 h earlier |

## *Early discharge scenarios*

Effecting early discharge is a widely recommended strategy for improving patient flow in hospitals. This approach quantified the impact of inpatient discharge timing on ED flow parameters and hospital beds utilisation towards understanding of a 'whole of hospital' response for patient flow improvement.[25] An algorithm (Algorithm 1) was devised to implement early discharge time scenarios (explained in details in Appendix S2).

Seven potential early discharge scenarios that were operationally and clinically feasible were defined following the analysis of the current discharge profile (as shown in Fig. C1 in Appendix S3) and in consultation with senior hospital administrators and the patient flow management team (Table 1).

The aim of these scenarios was to examine the impact of the following general discharge strategies: (i) emphasising early discharge by midday (i.e. Scenarios 1 and 4), (ii) targeting discharge completion by evening (i.e. Scenarios 2 and 3), (iii) spreading discharge throughout the day including evening (i.e. Scenario 5), (iv) discharging patients *N* hours earlier than their current discharge time (i.e. Scenarios 6 and 7).

## *Simulation model*

Our DES-based simulation consists of an ED module, an Inpatient module, and a Discharge module. Figure 1 shows a high-level conceptual model of our hospital-wide simulation. Emergency arrivals are processed within the ED module and the Elective arrivals, along with other admissions from ED (ED2IP encounters), are processed in the Inpatient module. Each ward was implemented as a separate resource with finite capacity, that is number of available beds. The capacity of each ward was obtained from monthly bed census reports during the study period. The queues were implemented using a first-in-first-out queuing strategy. However, emergency encounters were prioritised for access to the ED resources according to their clinical need as defined by the Australasian Triage Scale (ATS; https://acem.org.au/Content-Sources/Advancing-Emergency-Medicine/Better-Outcomes-for-Patients/Triage); the lower the ATS category the higher the urgency (ATS categories range from 1 to 5).

In our simulation, each patient arrival was defined as an event in the simulated environment. Patients arrived according to their actual arrival time and requested a bed at the admitting ward. If a vacant bed was available, this was allocated immediately, otherwise the patient waited in a queue and held the current bed (if in the middle of their journey) until a bed in the requesting ward became available. The waiting time was defined as the time from placement of an inpatient bed request at a target ward to the actual bed access (admission). Elective and ED2IP patients (encounters) were given similar priorities when waiting in a queue for an inpatient bed. After

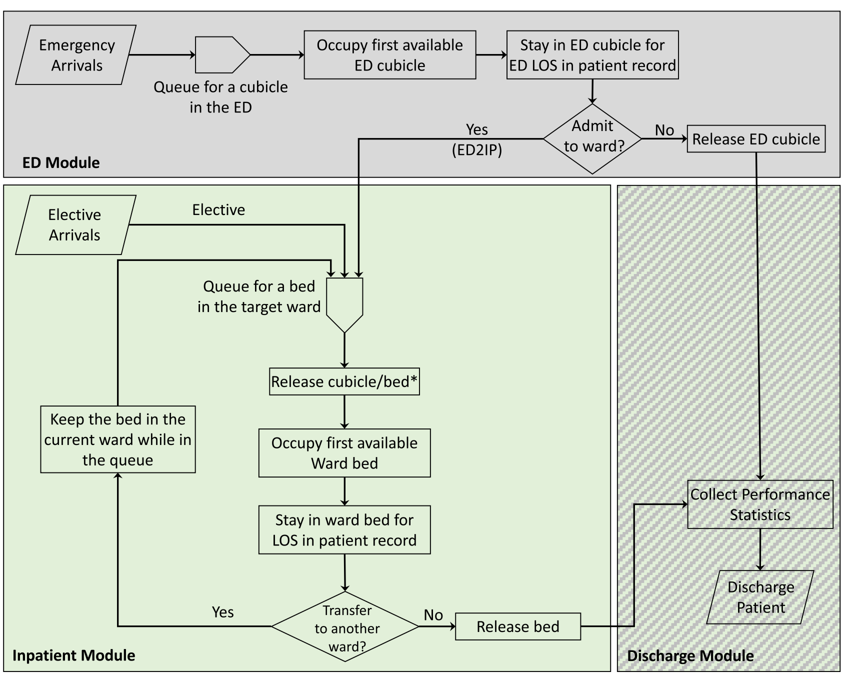


**Figure 1.** *Conceptual model of the hospital-wide simulation. *This step was not applicable for elective patients who were admitting to the first ward in their journey.*

a bed was assigned, patients kept the bed for a period of time defined by their LOS at that ward and then released the bed if they did not have any subsequent stay, or, as soon as they were able to move to the next location in their journey. A released bed immediately became available for other patients, not considering any bed preparation time. If patients had to wait in a queue for a bed to become available for their next movement, they stayed in their current bed (i.e. a waiting queue for a relocation was not considered as a separate space). These waiting times were calculated and collected in the Discharge module at the end of the simulation. Appendix S4 provides a schema of the model with indication of time of each event and Appendix S5 provides details of the model validation strategies.

### *Performance metrics*

Several ED-related and inpatient performance measures were used to quantify the impacts of various scenarios, including Average ED LOS, Total ED LOS, National Emergency Access Target (NEAT) compliance, Average waiting time for inpatient admission of emergency patients, and Bed Utilisation. These measures are defined in detail in Appendix S6. Given that the focus of the present study is to investigate the impact of bed configurations and early discharge timing on waiting times between emergency and inpatient departments, the reported ED-related measures in the next section (i.e. Average ED LOS, Total ED LOS, NEAT, and average waiting time) belong to ED2IP patients only. The first 6 months of the data was considered as the warmup period and the results were reported on the data for the 2019 calendar year.

This study was approved by the Queensland Health Hospital and Health Service Human Research Ethics Committee (HREC Ref No LNR/2019/QMS/51374) and CSIRO Health and Medical Human Research Ethics Committee (CHMHREC Proposal 2019_057_RR).

## Results

### *Bed configuration*

In order to investigate the impact of our clustering approach, we ran the simulation based on the capacities of the original wards but imposing the bed sharing (clustering) strategy. Table 2 shows different ED-related performance measures obtained from the simulated ward clustering and the actual (baseline) values observed during the 2019 calendar year. The table quantifies the anticipated performance improvements achieved by clustering but keeping the same number of beds. Although there were marginal changes in NEAT compliance and bed utilisation, the average and total ED LOS were considerably reduced by 21% compared to baseline. In addition, average waiting time was almost eliminated, reducing from approximately 61 to 1 min. Appendix S7 provides further analysis for comparing ED LOS between the baseline and ward clustering scenarios and indicates that the majority of ED LOS reductions were among the patients with longer stays (hence the minimal change in NEAT observed with clustering shown in Table 2).

Table 3 shows the results of simulation using the strategy of clustering of wards when targeting the same NEAT performance as obtained in the baseline data but varying the numbers of beds. By sharing beds across wards, this level of NEAT performance could be achieved with a relatively lower number of beds (16 beds less than baseline). In addition, average waiting time reduced from approximately 60 min (baseline) to approximately 40 min (clustering). Bed utilisation also increased from 80% (baseline) to 82% (clustering). Detailed results per cluster for a sample month are provided in Appendix S7.

### *Early discharge timing*

Table 4 summarises the results of different early discharge scenarios and their impacts on the performance measures compared to baseline performance. In general, all early discharge scenarios delivered only a marginal improvement in NEAT compliance (0.3–0.4% compared to baseline). There were more notable differences between scenarios, however, when considering the reductions in average ED LOS and average waiting time. Scenario 1 had the greatest reduction in the average patient ED LOS of 16%. The average patient waiting time was also considerably reduced by 75% after imposing Scenario 1 – that is a 45-min reduction in average waiting time. Bed utilisation decreased by 6.5% by discharging patients earlier. Such reduction in bed utilisation can indicate potential spaces to admit more patients after discharging patients earlier. Scenario 4 shows almost similar trends in performance measures as those in Scenario 1.

When compared to Scenario 2, there were more reductions in average waiting time in Scenario 3, which indicates the importance of

**TABLE 2.** *Summary of the impact of wards clustering on ED-related performance measures*

| | Beds | Bed utilisation | NEAT compliance | Average ED LOS (min) | Total ED LOS | Average waiting time (min) |
|---|---|---|---|---|---|---|
| Baseline | 427 | 79.7% | 69.0% | 284.6 | 9323 days, 11.19 hours | 60.5 |
| Ward clustering | 427 | 78.6% (−1.5%) | 69.4% (+0.7%) | 225.5 (−20.8%) | 7384 days, 20.33 hours (−20.8%) | 1.4 (97.8%) |

**TABLE 3.** *Cluster-level simulation results*

| Ward | Beds | Bed utilisation | NEAT compliance | Average ED LOS (min) | Total ED LOS | Average waiting time (min) |
|---|---|---|---|---|---|---|
| Cluster 1 | 102 | 92.3% | 8.7% | 607.3 | 1841 days, 17.02 hours | 39.7 |
| Cluster 2 | 55 | 86.7% | 20.6% | 455.3 | 334 days, 5.18 hours | 17.5 |
| Cluster 3 | 66 | 96.0% | 6.9% | 2289.8 | 1580 days, 14.14 hours | 1630.1 |
| Cluster 4 | 39 | 72.4% | 79.8% | 148.8 | 3213 days, 19.26 hours | 0.4 |
| Cluster 5 | 26 | 66.3% | 79.3% | 176.1 | 1028 days, 16.46 hours | 4.2 |
| ICU | 7 | 73.1% | 30.3% | 428.2 | 57 days, 23.42 hours | 1.2 |
| 2D | 30 | 75.2% | 34.1% | 370.9 | 11 days, 8.01 hours | 15.6 |
| MAC | 4 | 50.0% | 60.6% | 213.2 | 4 days, 21.15 hours | 50.6 |
| PAL | 8 | 87.3% | 27.0% | 919.2 | 63 days, 20.02 hours | 101.6 |
| REH | 24 | 79.8% | 20.0% | 373.6 | 2 days, 14.16 hours | 0 |
| CID | 4 | 21.2% | 0.0% | – | – | – |
| 2 dB | 30 | 51.0% | 0.0% | – | – | – |
| SCN | 16 | 85.3% | 0.0% | – | – | – |
| OTHER | – | – | 29.9% | 836.6 | 500 days, 5.35 hours | 0 |
| Total | 411 | 81.8% | 69.0% | 263.8 | 8639 days, 21.42 hours | 39.7 |

**TABLE 4.** *Summary of the impacts of early discharging scenarios*

| | Bed utilisation | NEAT compliance | Average ED LOS (min) | Average waiting time (min) |
|---|---|---|---|---|
| Baseline | 79.7% | 69.0% | 284.6 | 60.5 |
| Scenario 1 (50% by 10.00 hours, 80% by 12.00 hours, 100% by 14.00 hours) | 74.5% (−6.5%) | 69.3% (0.4%) | 239.2 (−16.0%) | 15.1 (−75.0%) |
| Scenario 2 (35% by 11.00 hours, 70% by 14.00 hours, 100% by 17.00 hours) | 76.8% (−3.6%) | 69.2% (0.4%) | 251.1 (−11.9%) | 27.0 (−55.4%) |
| Scenario 3 (50% by 11.00 hours, 70% by 14.00 hours, 100% by 17.00 hours) | 75.8% (−4.9%) | 69.3% (0.4%) | 243.9 (−14.3%) | 19.8 (−67.4%) |
| Scenario 4 (80% by 11.00 hours) | 75.4% (−5.4%) | 69.2% (0.4%) | 241.2 (−15.3%) | 17.1 (−71.8%) |
| Scenario 5 (40% by 10.00 hours, 70% by 14.00 hours, 90% by 17.00 hours, 100% by 22.00 hours) | 75.6% (−5.1%) | 69.3% (0.4%) | 243.4 (−14.5%) | 19.3 (−68.1%) |
| Scenario 6 (Discharge all patients 1 h earlier) | 77.8% (−2.4%) | 69.2% (0.3%) | 256.5 (−9.9%) | 32.4 (−46.5%) |
| Scenario 7 (Discharge all patients 2 h earlier) | 76.4% (−4.1%) | 69.3% (0.4%) | 249.5 (−12.3%) | 25.4 (−58.0%) |

having higher discharge rates in mornings; the only difference between the two scenarios was on discharging 35% by 11.00 hours in Scenario 2 *cf*. 50% by 11.00 hours in Scenario 3. Such an impact was also observed in the waiting time reduction in Scenario 5.

Discharging patients 1 h earlier than their actual discharge time in Scenario 6 had the least impact on LOS, waiting time and NEAT performance. Bed utilisation, however, had its highest value in Scenario 6 compared to the rest of the scenarios. For Scenario 7, NEAT improvement was similar to Scenarios 3 and 5, but the impact on average ED LOS and average waiting time was not as great as Scenarios 3 and 5. Overall, bed utilisations reduced by up to 7% and NEAT compliance was marginally higher in all assessed scenarios compared to the baseline setting.

## Discussion

### *Impact of clustering wards*

The simulation modelling revealed that the current ward-level performance can be achieved with a lower number of beds when patients are admitted to a common set of shared beds in a cluster as opposed to when they are admitted to separate individual wards. By clustering beds together, bed utilisation increased and the number of beds required to deliver current flow performance decreased. For example, by clustering 'Medical' wards comprising 3A, 3B, 3C, 3CCARD, AMU and MAPU together, bed utilisation increased by 4% and five fewer beds were needed to deliver the same NEAT compliance level. Clustering Mental Health wards together resulted in nine fewer beds being required. Clustering beds resulted in a reduction in total ED LOS, although a marginally larger average queue length was formed as patients formed a single queue in cluster-level simulation (data not shown).

Combining wards into clusters has been mostly approached as an optimisation or a queuing theory problem in the literature.[26–28] Although these approaches are different from our DES-based methodology, the findings are similar in that the number of beds that are needed to maintain a given patient flow performance can be reduced by a clustering approach.

### *Impact of early discharging*

In Scenario 1, ED LOS was reduced by 16%, whereas average patient waiting time was reduced by 75% (corresponding to a 45-min reduction). Similar potential gains in flow performance were found with Scenario 4. This alternative scenario may, however, be more difficult to operationalise, as it burdens a single staffing shift with the responsibility of the discharge target, instead of spreading it out across the day.

Scenarios 2, 3 and 5 explored targets spread across the day that are arguably easier to achieve, but still delivered greater improvements in flow compared to scenarios exploring discharging all patients 1 h earlier (Scenario 6) or 2 h earlier (Scenario 7). Previous research has also suggested that such 'blanket approach' scenarios are harder to operationalise than time-based targets and they are likely to be impractical.[25] It is interesting that superior flow performance can be realised through targeting one of the alternative more feasible discharge time targets. The study also explored the impact of these discharge scenarios at a ward level, identifying wards where efforts need to be targeted for maximum impact. The modelling supports the use of time-based discharge targets to improve patient flow. A suggestion is the use of ward-level hourly discharge profiles (as presented in Fig. C1 in Appendix S3) to inform decision making in selecting or defining discharge time targets.

### *Limitations*

One of the limitations of our study was that we were not able to design an experiment to reach a theoretical maximum ED performance based on the key performance metrics. This was because of a limitation in the data. Inpatient ward capacities can only directly affect the bottleneck between ED and inpatient wards, or more specifically, the waiting time for ED patients requiring admission ('ED2IP' patients). Thus, the maximum possible improvement in ED performance for admitted patients achievable by modifying downstream capacity is when we completely eliminate inpatient admission waiting time for these patients. However, on investigation, the 'Departure Ready' timestamp (the start clock of ED2IP patients' waiting time) was discovered to occur only 1 min before the 'Actual Departure' timestamp (the end clock of waiting time) for the majority of ED2IP encounters. Given that the simulation model is trained on this actual data with its limitations, it is not practical to try and model scenarios to achieve higher performances. Although this is not practical in a retrospective analysis, it should be mentioned that a simulation with synthetic data enables implementing scenarios where higher performances can be tested.[18]

Simulation was based on historic data patterns of patient movements and guided by clinical flows which reflected actual lengths of stay in each ward (as opposed to arbitrarily generated time points) and a 1-year timeframe for simulation assessed in the present study is reasonable to capture underlying variation in these ward movements. However, care pathways within a hospital are dynamic (certainly the COVID-19 pandemic has changed many) and similar modelling is recommended for all hospitals using the latest data available. Although we attempted to incorporate realism when modelling internal hospital flows, several assumptions were made. For example, adopting a strategy that as soon as a bed was vacated it became available to accept a patient requiring a bed in that ward; setting discharge times to be distributed uniformly over a certain time period before the target discharge time; and the grouping of wards based on both their clinical/treatment purpose and location within the hospital. Although there is some basis for these assumptions, there may be unforeseen constraints that impact the translation of modelled improvements to lived experience when implemented.

Our simulation approach provided a hospital-wide model by only considering inpatient beds as resources. Hospital staff is another type of resource, the availability of which can directly impact patient flow and key performance metrics. Although including clinical staff as another set of resources can result in a more detailed model, this may introduce complexities that can detract from the accuracy of a DES-based model because of the dynamics in rostering systems across days, weeks, or months. A hybrid approach of DES and agent-based simulation might provide a more appropriate solution to model such levels of complexity.

## Conclusions

The present study showed that cluster-level bed configuration enabled maintaining similar performance metrics as in the baseline setting whereas using fewer beds. The reported results of simulating early discharge scenarios quantified the potential improvements in patient flow that can be realised by discharging admitted patients earlier in the day. The findings reinforce the benefit of time-based discharge targets to improve patient flow.

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### *Competing interests*

None declared.

### *Data availability statement*

Data analysed in the present study is unable to be shared because of legislative and review committee requirements. The original data are available from Queensland Health subject to appropriate governance and ethical approvals.

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## Supporting information

Additional supporting information may be found in the online version of this article at the publisher's web site:

**Appendix S1.** Patient movements during hospital stays.

**Appendix S2.** Early discharging algorithm.

**Appendix S3.** Current discharge profile.

**Appendix S4.** Simulation model schema.

**Appendix S5.** Model validation.

**Appendix S6.** Performance metrics and experimental setup.

**Appendix S7.** Detailed clustering results.