Virtual Evaluation of a Hospital Congestion Prevention Method

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Research

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Abstract

Background: Hospital congestion is a common problem for the healthcare sector. Numerous studies explored reasons for crowding within some parts of the hospital. However, to deal with more general, hospital-wide problems, examining the hospital as a connected whole is necessary. The purpose of this study was to evaluate de-congestion interventions through a whole hospital simulation model and offer objective reasoning to support hospital management decisions.

Method: This study tested a congestion prevention method that estimates the current day's hospital congestion risk level R at a set time every morning, and activates minimum intervention when R is above certain threshold R(C), using a virtual hospital created by simulation modelling. The color-coding system was adopted to demonstrate the impact and the extent of effectiveness of this method in preventing hospital congestions.

Results: The results indicated that adding 8 flex beds to the medical department resulted in more reductions (70.93%) of red-days comparing with the surgical ward (37.15%). Red days reduction per affected patient when discharging two medical patients was 0.1 which was higher than when discharging two surgical (0.04) or two long-stay patients (0.07). Also, the efficiency

of red days reduction per affected patient is always greater if removing 2 patients than if discharging more patients.

Conclusions: The expected outcome based on theoretical prediction of this method was confirmed, that is, applying a less disruptive intervention is often enough, and more cost effective, to reduce the risk level of hospital congestion. Making a small number of extra beds available was a superior solution compared to discharging approaches to reduce crowding in hospitals. In addition, the virtual implementation approach enabled testing of the method at a more detailed level, thereby revealed some interesting findings difficult to achieve theoretically, such as discharging extra two medical inpatients, rather than surgical inpatients, a day earlier on days when R>R(C), would bring more benefits in terms of congestion reduction for the hospital.

Key words: Hospital congestion, Simulation model, Virtual implementation, De-congestion interventions, Management decision

Contribution to the literature

- This research tested a congestion prevention method involving potential interventions within a virtual complex system and offered objective reasoning to support hospital management decisions.
- For each intervention the simulation results demonstrated not only its effectiveness in preventing hospital congestion but also the extent of impact upon patients.
- The expected outcome based on theoretical prediction of this method was confirmed, that is, applying a less disruptive intervention is often enough, and more cost effective, to reduce the risk level of hospital congestion.

1. Background

The shortage of public hospital resources in Australia is becoming a major concern in this modern era due to increasing patient demands. More hospital congestion episodes accompanied by longer waiting times and queueing length in the Emergency Department (ED) have been associated with a greater risk of hospital-acquired infections, public complaints and, possibly, negative impacts on hospital staff mental health [1,2]. These adverse outcomes could get worse hence there is an urgent need to find effective ways to reduce overcrowding and congestion in our hospitals.

Recent studies have sought solutions from various perspectives and with various approaches. A considerable amount of attention has been directed to explore reasons for crowding within some parts of the hospital, particularly the ED, aiming to reduce access block through improving ED performance [4-8]. Each of these studies has successfully improved congestion problems for the hospitals concerned. However, to deal with more general, hospital-wide problems, instead of focusing on a particular department, examining the hospital as a connected whole is necessary. This is because a hospital is a complex system and composed of different parts that involve diverse factors and stochastic processes. The complicated interactions among these parts must be taken into consideration.

In terms of methodology, there have been many studies attempting to identify reasons for hospital congestion and improve the efficiency of hospital operation using analytical approaches. Two examples of these approaches are regression modelling and time-series modelling [9-10]. Undoubtedly, it is quite challenging for researchers to model a whole hospital only through analytical methods, due to its structural and behavioral complexities [11]. Thus,

when it comes to predicting the dynamic behaviour of a hospital and estimating the short- and long-term effects of potential interventions, numerical analysis-based methods often involve complicated concepts and algorithms that are not interpretable by healthcare professionals.

Computer simulation has been adopted by some researchers because it shows unprecedented advantages for tackling the complex problems of the health-care sector. Its flexibility and ability allow researchers to handle the variability, uncertainty, and complexity of a dynamic system [12]. Simulation is particularly useful when problems involve stochastic processes. It is also an ideal tool to examine system-wide consequences of changes in one or more areas of the hospital in a risk-free environment. Hence, a virtual hospital is deemed to be the best environment to test potential improvement strategies, methods and tools through what-if analysis, which also leads to more comprehensive and in-depth insights than what can be achieved with analytical methods [13].

This paper introduces a case study using a simulation model named HESMAD (Hospital Event Simulation Model: Arrivals to Discharge) [13] developed to represent an end-to-end patient flow process of a typical large Australian public hospital. Through virtual implementation of the congestion prevention method and monitor its impact using the simulation model, this study demonstrates, with highly detailed simulation results, the effectiveness of both the prevention method and the virtual implementation approach. In the rest of this paper, section 2 mainly introduces the methods. Section 2.1 describes the congestion prevention method. Section 2.2 introduces the HESMAD model which can be regarded as a virtual hospital for investigating decongestion interventions. In section 2.3, the congestion prevention method was virtually implemented in the simulation model to investigate its impact with different patient flow

scenarios. Section 3 exhibits the simulation results so that the solutions can be compared and considered for real-world disposition. Discussions and conclusions are presented in section 4 and 5.

2. Methods

2.1 A hospital congestion prevention Method

This section introduces a research-based congestion prevention method based on a concept named "hospital's instability wedges" [3]. The concept demonstrates, theoretically, that the risk of patient flow congestion can be calculated on a daily basis and prevention can be achieved by activating interventions that involve very small number of patients when the risk level is deemed high. This leads to a potentially effective method for real-time congestion prevention.

The typical scenario in a hospital is that, on a daily basis, patients arrive at the ED. Some patients are discharged from the ED and some admitted. Hospital-wide, inpatients are discharged after a period of stay, and a variable number of planned or elective admissions occur. These processes compete for limited resources and congestion episodes occur when bottle necks appear. The method first estimates the risk of congestion R at a set time every morning, using the current hospital occupancy and predicted patients' admission and discharge numbers based on the day-by-day variation patterns derived from the hospital's history data, and activates minimum intervention when R is above certain threshold R(C). Specifically, the method allows us to calculate the risk that the current day's midnight occupancy (M_t) exceeds a specified threshold, denoted by C. The threshold C was set as the hospital's normal bed capacity in this study. The probability of such exceedance $R(C)$ was calculated by the following equation:

$$R(C) \approx P(M_t > C) \tag{1}$$

In order apply this approach to control the risk of hospital congestion, this formulation has been refined to become more implementable and controllable for decision-makers. The following equation was considered at the beginning:

$$M_t = \eta_t N_t + E_t(1 - \omega_t) + M_{t-1}(1 - v_t) \tag{2}$$

Where N_t indicates the new arrivals at the hospital ED on the day. E_t is defined as the elective patients scheduled to stay in the hospital at least one night. M_{t-1} is the midnight occupancy of the previous day. $\eta_t \in (0, 1], \omega_t \in (0, 1], v_t \in (0,1]$ denotes the admission rate of the new arrivals, cancelled elective patients and inpatients discharged, respectively.

The following task is to investigate the dependence of the congestion risk *R(C)* on η_t, ω_t and v_t which are treated as control parameters. Due to the fact that N_t is the only random variable on the right-hand side of equation 2, the equation 1 was refined as follows:

$$\begin{aligned} R(C) &= P(M_t > C) \\ &= P\left(N_t > [C - M_{t-1}(1 - v_t) - E_t(1 - \omega_t)]\frac{1}{\eta_t}\right) \end{aligned} \tag{3}$$

As a result, R(C) became the simplified notation $\mathrm{R}(\mathrm{C}, \eta_t, \omega_t, v_t)$ which is composed of the control parameters. Since N_t is random, the negative binomial distribution and the normal distribution were employed to fit the histogram exhibited in Figure 1.

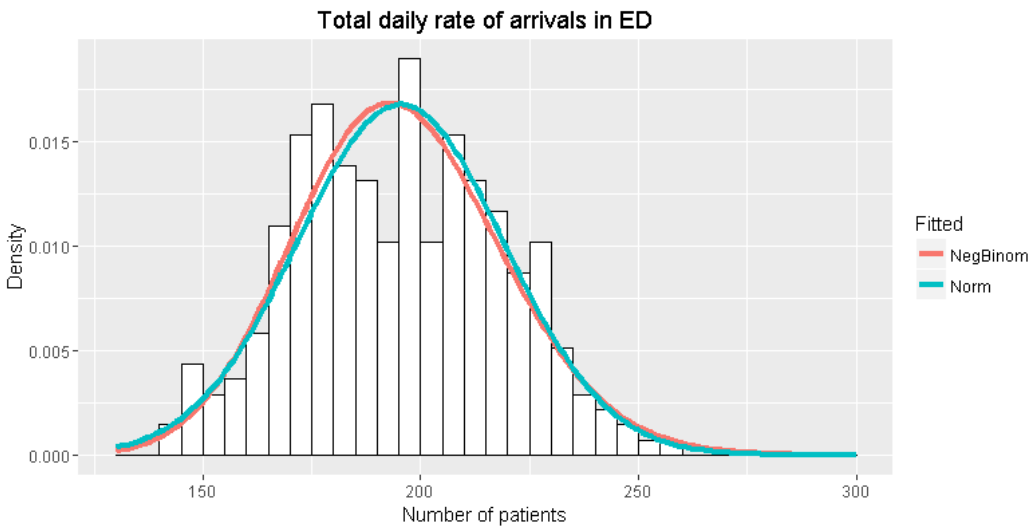

Figure 1 Histogram of N_t and two matched distributions. Source: Ben-Tovim et al [3].

Equation 3 can be refined again based on the simple restriction $\omega_t = 0$:

$$R(C) = r(C, \eta_t, 0, \nu_t) = P(N_t > x_t) = 1 - \Phi(x_t; \mu_t, \sigma_t^2) \quad (4)$$

where $x_t := [C - M_{t-1}(1 - \nu_t) - E_t] / \eta_t$, μ_t and σ_t^2 are the mean and variance of the population of arrivals in the ED on the selected day of the week and $\Phi(x; \mu, \sigma^2)$ denotes the probability distribution function of the normally distributed random variable $X \sim N(\mu, \sigma^2)$. Consequently, R(C) can be easily calculated based on the equation above.

The bright spot of this method is that it allows decision-makers to change the control parameters to prevent hospital congestion when the congestion risk R(C) is high. That is to say, if we adjust the threshold C or the rate of admitted η_t or discharged patients ν_t, R(C) will be changed accordingly.

Figure 2 illustrates the R(C) change of an example with different admission and discharge rates (M_{t-1} = 595, E_t = 28, C = 600). The horizontal and vertical axes represent admission rates $\eta_t \in (0, 1]$ and discharge rates $\nu_t \in (0,1]$ respectively. The solid green indicates low risk values and the red area indicates high risk values. The thin wedge named "hospital instability wedge" is indicated by the colors changing from solid red to green [3]. In Figure 2, it has been found that

the thinner the wedge, the more sensitive is the risk R(C) changing from red to green. Theoretically, smaller changes in the numbers of admitted or discharged patients exhibit more effective and sensitive impacts on R(C) which indicates the probability of hospital congestion occurrences because of the relative thinness of the wedge.

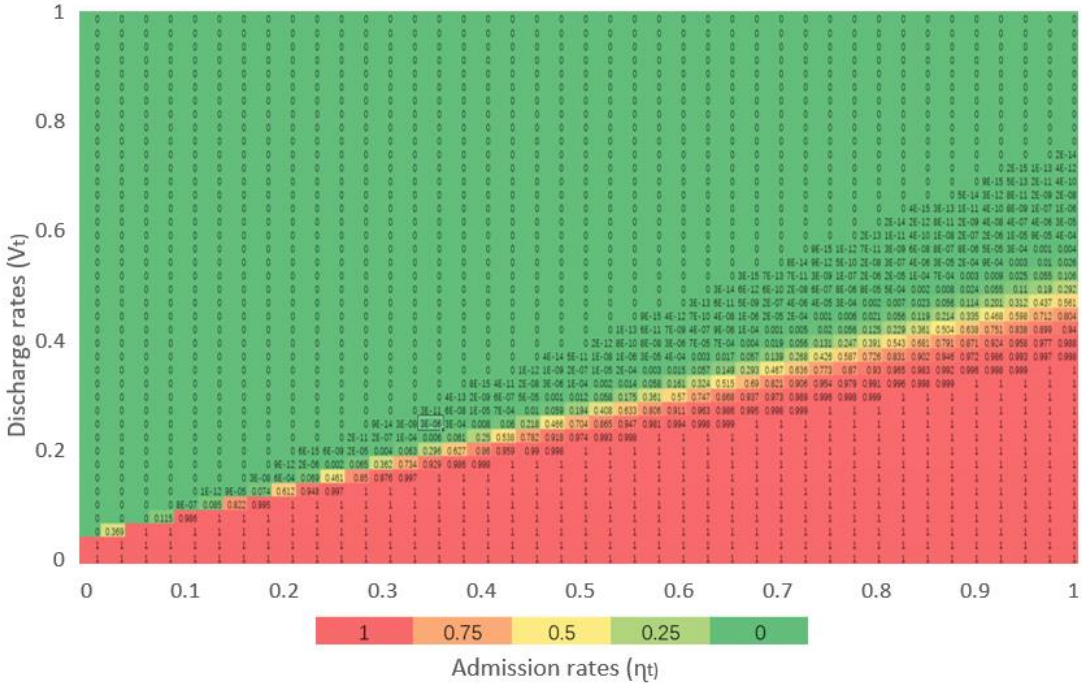

Figure 2 The change of R(C) with different admission and discharge rates

We assumed that hospital managers check the congestion risk using this method in the morning and start to plan for the day. If the risk rate is extraordinarily high in the morning, the probability of congestion occurrence might also be high during the day. Therefore, managers will plan to make an adjustment to the number of admissions or to discharge a few patients to weaken this discordant possibility. Relying on the above method using historical patient flow data allows us to understand the change of congestion probability R(C) when interventions are adopted. However, it is impossible to demonstrate the expected, but more intuitive and quantitative, impacts on congestion episodes by the method. Moreover, when managers attempt to manipulate different numbers of patients for congestion prevention, other issues might emerge

including the type of patients or department that should be the focus for the intervention(s). In other words, from a managerial perspective, the type of patients affected by an intervention can impact on de-congestion effectiveness. Smaller adjustments affecting several different types of patients may be more effective and sensitive in reducing congestion risk. To address these issues, simulation modelling carries an advantage due to the fact that it provides a risk-free platform to help stakeholders access changes in operations, managerial policies and examine different alternatives. Through implementing the method and designing more specific indicators for hospital congestion based on the HESMAD simulation model, the impacts of interventions on congestion prevention were investigated explicitly and in depth.

2.2 Hospital Simulation Model

This study was based upon work-flows through a large Australian metropolitan hospital previously re-designed to improve efficiency and the quality of patient care by using Lean Thinking [3,15,16]. Aiming to provide a safer and more accessible service is not a simple task for the healthcare system because hospitals are complex and dynamic. To achieve hospital service improvement, a comprehensive modeling of this complex system was undertaken in order to imitate the dynamic behaviours necessary for, and consequent to, each theoretical intervention.

We have developed Hospital Event Simulation Model: Arrivals to Discharge (HESMAD) to explore the dynamics of patient flows for this hospital [13]. Undoubtedly, constructing the model at a macro level allows researchers to investigate stochastic processes and further design interventions for dealing with congestion issues.

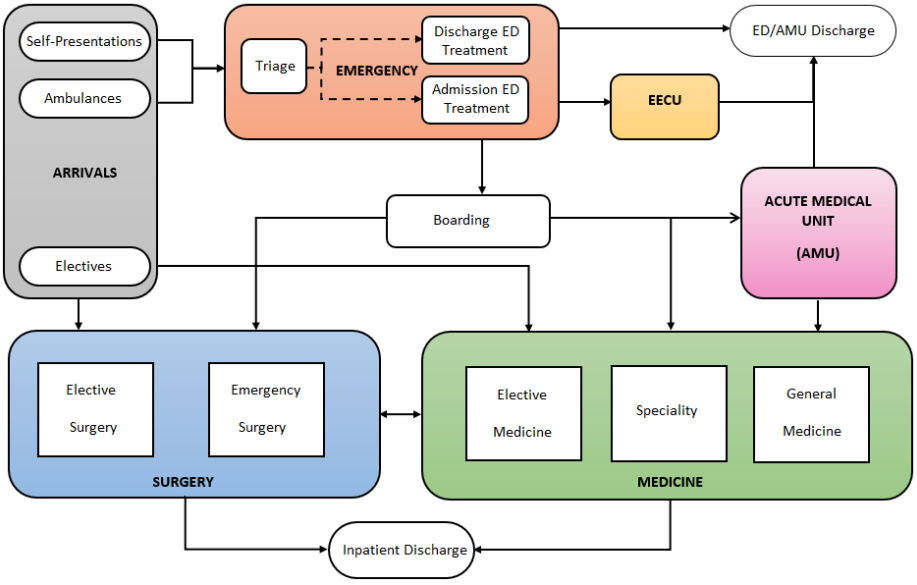

Figure 3 Overview of the HESMAD structure. Source: Ben-Tovim et al [13].

Figure 3 shows the structure of HESMAD. The model was constructed to simulate behaviours of the hospital as realistically as possible. It contains several components representing emergency admissions, elective admissions, inpatients and discharge.

Different types of patients go through physical units which were represented as modules in the model. All processes, interactions and behaviours between patients and the hospital were included in each module to imitate patient journeys.

The linked modules catch patient pathways when they go through the physical units in the hospital as described in Table 1. The process begins when all patients except electives arrive in the ED. A triage score is assigned to indicate the severity of patient condition and to decide treatment stream and queuing priority. Some patients are discharged when they finish ED treatment. Other patients are admitted into the hospital inpatient units. In the inpatient departments, 330 base beds and 8 flex beds were modeled in the simulation model. Patients are placed in a queue when beds are not available in relevant treatment areas. Probability distributions obtained from historical data were used to reflect patient state and their LOS in

different areas of the hospital. The final process of discharging patients involves releasing resources. Monitoring different indicators such as the number of beds occupied allows one to evaluate hospital congestion and investigate the potential influence of strategical interventions on hospital overcrowding.

2.3 Simulation-based evaluation

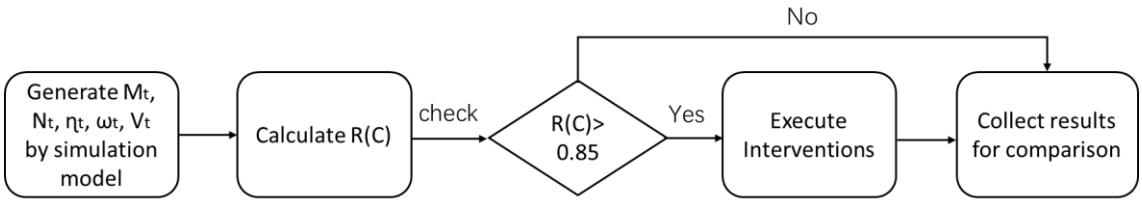

Figure 4 Process of the simulation-based evaluation

In order to clarify the decongestion effects of different strategies more thoroughly, the intervention ideas from the method were transcribed into scenarios for investigating in the simulation model. Furthermore, a color-coding system was also adopted for each scenario evaluation before, during and after hospital overcrowding.

The process of this simulation-based evaluation is illustrated in Figure 4. We assumed that hospital managers check the congestion risk using the method in the morning and start to plan for the day. When R(C) exceeded 0.85, managers could add beds or cancel operations on a few patients for that particular day. In the simulation platform, the same process was realized. The model calculates R(C) in 8:00 am every day. If R(C)>0.85, the intervention is executed for that day. All parameters used for R(C) calculation are generated by the simulation model on a daily basis.

2.3.1 Threshold scenarios

The threshold was defined as the hospital capacity in the risk prevention method in this study.

219 In this large tertiary hospital, there are 330 base beds including 170 medical beds, 130 surgical
220 beds and 30 AMU beds in separate inpatient departments. 8 flex beds can be arranged when the
221 hospital is nearing exhaustion of its finite capacity. Using the congestion risk prediction method,
222 the impacts on congestion prevention of using flex beds to change the threshold number
223 (Scenario 1-4) were estimated by the HESMAD model. Furthermore, the department to which
224 the flex beds are added (scenario 5, 6) can influence decongestion efficiency (Table 2).

225 2.3.2 Discharge scenarios

226 Discharging patients was considered as a way to reduce the risk of hospital crowding. In the
227 simulation platform, this intervention was transcribed into different scenarios to test its effects
228 on hospital congestion. However, the type of patients more likely to impact on congestion could
229 be an issue and smaller adjustments for different types of patients may be more effective and
230 sensitive in congestion prevention. To address these issues, an intervention that only
231 implements discharge operations through the tool is not sufficient. Therefore, interventions on
232 different types of patients were executed by the simulation model on a daily basis but only when
233 the congestion risk rate reaches or exceeds 0.85 (Scenario 10-21) at 8 am each day (Table 3).
234 From an ethical aspect, those patients who have recently started treatment are not considered
235 for discharge. The model only discharged patients who have 1 day left of their hospital stay.
236 The simulation model generates patients who were assigned all information including Length
237 of stay and personal information related to the whole treatment process, therefore, discharging
238 patients 1 day earlier is easily realized. Since this study concentrates on the congestion
239 prevention of differing inpatient departments, the model was adjusted for inpatients including
240 medical, surgical and long stay patients (Table 4) by relevant transcription into the scenarios in

241 the model.

242 A color-coding system, similar to traffic signals used by SA Health to trace hospital
243 overcrowding status, was adopted into the HESMAD on a daily basis [16].

244 - Green day means that the hospital has at least 10% of total inpatient beds available.
245 - Amber day means that the hospital has between 3% and 10% of total inpatient beds
246 available.
247 - Red day means that the hospital has less than 3% of total inpatient beds available.

248 The accumulated numbers of green, amber and red days were collected finally to indicate the
249 congestion situation. Also, the midnight hospital occupancy, R(C), and the number of patients
250 affected by each intervention were recorded every day for each simulation-based evaluation.
251 Each simulation run for 2 years. Results of the second year were collected for analysis to
252 minimize the effect of the 'warm-up' period of the first year. In addition, each scenario was
253 replicated 20 times under the same conditions to obtain an average behaviour that would allow
254 meaningful comparison of the results from different intervention scenarios. Minimizing the
255 number of red days was the goal for the different interventions. The reduction in the number of
256 red days per affected patient was also calculated to estimate the efficiency of each scenario
257 whereby the efficacy of each intervention is related to its disruption to patient care. The result
258 comparisons are exhibited in Table 5.

259 **3. Results**

260 The base case scenario in Table 5 is the baseline for the result comparisons of different
261 interventions. The results of Scenario 1-6 indicated that the occupancy increased slightly when
262 the total bed capacity increased. The number of red days decreased from 79.95 to 53.1 when 2

263 flex beds were added to inpatient departments (scenario 1) compared to base case scenario. The
264 more flex beds were added, the greater the reduction in red days. Especially when 8 flex beds
265 added (scenario 4), the number of red days decreased to 37.3. By contrast, the number of green
266 days changed from 33.45 to 107.35 days when elevated threshold interventions were executed
267 (scenario 1-4). The number of amber days decreased accordingly while implementing scenario
268 1-4. This was a non-linear decrement because the number amber days of scenario 3 was 240
269 which increased slightly compared to scenario 2. Adding 8 flex beds to the medical department
270 (scenario 5) resulted in a 70.93 % reduction of red-days comparing with the base-case scenario
271 (scenario 0). However, adding 8 beds to the surgical ward (scenario 6) only achieved a 37.15%
272 reduction in red days.
273 Scenario 7-10 focused on the effects on hospital congestion over a one-year period of earlier
274 discharges of different numbers of inpatients. According to Table 5, the midnight occupancy
275 decreased from 311.8 to 308.57 while discharging 2-8 inpatients. Discharging 2 inpatients
276 (scenario 7) when R(C) exceeds 0.85 resulted in a 15.63% decrease in red days compared to
277 base-case scenario (scenario 0). Discharging 4 (scenario 8) inpatients is able to reduce red days
278 by approximately 20.7% from 79.95 to 63.4. Discharging more inpatients generated 24.08%
279 and 31.52% of red-days reduction respectively in scenario 9 and 10. Differing from threshold
280 scenarios, the amber days increased from 250.6 to 260.8 when 2-8 inpatients were discharged
281 (scenario 7- scenario 10). These scenarios also offered increases of 31%, 35%, 41% and 45%
282 in green days respectively.
283 The midnight occupancy decreased from 311.8 to 304.45 while executing scenarios 11-14.
284 Discharging medical patients produced greater levels of red-days reduction compared to other

discharging scenarios. Removing 2 medical patients when R(C) exceeds 0.85 led to a 34.7% reduction in red days (scenario 1). Particularly discharging 8 medical patients generated a 48.66% reduction in red days. Amber days increased 6.46%, 9.18%, 9.72% and 8.54% respectively when 2-8 medical patients were discharged. Discharging medical patients also achieved a green days increase from 33.45 to 97.

For surgical patients, these discharging interventions maximally reduced red days by 21.01% (scenario 18). Removing 2-8 surgical patients (scenario 15-18) can boost the number of green-days from 38.5 to 54.2 days compared to 33.45 in the base case scenario, but these particular interventions had only a limited impact on the number of amber days. The midnight occupancy was decreased from 311.8 to 309.41.

Removing 2 and 4 long stay patients when R(C) exceeds 0.85 resulted in 11.94% and 19.82% reductions of red days. The number of amber days slightly increased. Also, the number of green days increased 23% and 36% respectively when 2 and 4 patients were discharged. These two scenarios demonstrated the limited impacts of these interventions on midnight occupancy (311.8 to 310.19).

Red days reduction per affected patient was also calculated to evaluate the efficiency of each scenario in Table 4. Red days reduction per affected patient when discharging two medical patients was 0.1 which was higher than when discharging two surgical (0.04) or two long-stay patients (0.07). This suggests that a discharge strategy is more effective and less disruptive if medical patients are discharged. The other discovery was that for all discharging scenarios, the efficiency of red days reduction per affected patient is always greater if removing 2 patients than if discharging more patients.

4. Discussion

This study embedded the congestion prevention method in the simulation model to investigate the potential impacts of different approaches on hospital overcrowding. It also demonstrates that piloting interventions in a virtual environment allows us to further understand major influences on hospital congestion. It is a fact that the congestion risk calculation method is able to predict the probability of congestion occurrence. However, using the simulation model allows us to test the impacts of a variety of interventions in depth and to safely compare the cumulated effects of different approaches.

This study adopted a colour-coding system which is similar to traffic signals to describe the status of hospital overcrowding and used it for results comparison of different scenarios. It is demonstrated that the number of red-days declined significantly when flex beds were added to inpatient departments. Also, threshold scenarios were more effective for red day reductions than discharging scenarios. For instance, compared to 54.75 red days occurring per annum after discharging 8 patients in response to every day of high congestion risk, the number of red days occurring per annum was much lower (37.2) if the intervention was adding 4 beds to each of the medical and surgical inpatient departments. In a nutshell, adding beds is preferable to discharging patients. We considered that an additional bed facilitates patient flow. In other words, adding a bed might benefit a considerable number of patients during a period of hospital congestion. However, discharging patients seems to have fewer effects because it only involves a small number of discharged patients and hence might only slightly influence hospital overcrowding. Another interesting discovery is that adding 4 beds and 6 beds have very similar effects on red-days reductions. One possibility is that some patients waiting in the queue are

329 admitted to these additional beds which sustains the occupancy, consequently, the red-days gap
330 between adding 4 beds (scenario 2) and 6 beds (scenario 3) is not obvious. Further increasing
331 flex beds above six leads to more reductions of red-days compare to scenario 2 and 3.
332 Adding beds especially in the medical department brings more expected benefits in respect of
333 congestion reduction for the hospital. Also, discharging medical patients rather than surgical
334 patients brings benefits in respect of congestion prevention and leads to impressive red-days
335 reduction and elevations in the numbers of green-days. To seek to understand this phenomenon,
336 by tracing the historical data in Table 6, it has been found that there were 21773 medical patients
337 receiving treatment in the medical department for one year which accounted for the total
338 numbers of 46.3% of the total number of patients attending this hospital. Surgical patients
339 numbered 13630, or 29% of the total. There are 17.3% more medical patients than surgical
340 patients. In addition, LOS distributions of medical and surgical patients are demonstrated in
341 Figure 5. The horizontal axis shows the LOS of inpatients. The vertical axis presents the
342 proportion of patients with different LOS. There are about 94% of medical patients and 97% of
343 surgical patients whose LOS are less than 21 days. The proportion of medical patients whose
344 LOS exceeds 21 days is higher than that of surgical patients. The total period of time where
345 hospital beds are occupied by medical patients for one year is longer than surgical patients.
346 Consequently, we believe that medical patients contribute to hospital congestion more
347 significantly than other types of patients. When interventions are implemented for medical
348 patients and medical departments, the effect on red days reduction is more obvious.

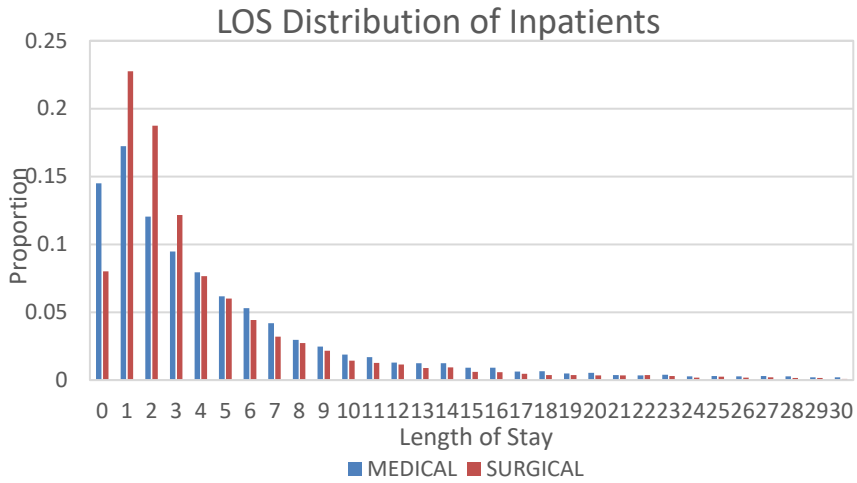

Figure 5 LOS Distribution of Inpatients

In this study, the cumulated numbers of red days, amber days and green days for each one-year simulation period were recorded based on the colour-coding system. A reduction in the number of red days is the common goal of all interventions. However, for the change of amber days and green days, we still need to discuss further. In the face of a reduction in red days, there are three patterns of change possible for the number of amber and green days (Table 7). If, when red days decrease, an intervention can lead to amber days decreasing and green days increasing, this suggests decongestion is occurring. But this might be construed as inefficient in terms of a resourcing perspective. From the utilization efficiency point of view, the preferable operating pattern of the hospital is that resources are utilized as much as possible while patients can still flow smoothly. That is to say, a more desired consequence of decongestion or red day reduction is an increase in the numbers of both amber days and green days, such as pattern 2 in Table 7. It has been seen that amber days increase, but green days decrease in pattern 3 in Table 7. In this case, decision-makers should consider some parameters such as queue length of patients waiting for the treatment and midnight occupancy to confirm patients still flow smoothly. Otherwise, this latter pattern of intervention has a limited effect on hospital overcrowding.

366 Discharging inpatients (scenario 7-10) especially discharging 2 surgical patients (scenario 15)
367 and long-stay patients (scenario 19-20) will slightly increase amber days which belongs to
368 pattern 2 in Table 7. From the utilization efficiency perspective, those interventions are
369 preferred to an intervention such as scenario 16.
370 We also calculated the ratio of the reduction in red days expressed relative to the number of
371 patients affected by each intervention and we called this the efficiency of each scenario. We
372 discovered that for different types of patients, red days reduction per affected patient when
373 removing fewer patients is always more favourable than when discharging more patients. This
374 finding confirmed "the hospital instability wedge" phenomenon which demonstrates that a less
375 disruptive intervention applied may be a more cost-effective way to address congestion risk.
376 At the beginning, random discharging interventions were designed to validate the simulation
377 model [13,16]. Therefore, discharging patients occurred throughout the whole simulation
378 period. Also, patients might unrealistically be discharged when they had only recently been
379 admitted. Thus, the midnight occupancy would drop significantly in those other studies unlike
380 the present study. In the present study, the congestion prevention method was adopted to
381 calculate R(C) which provides the condition to execute a range of interventions. The value of
382 0.85 was selected as the threshold for scenarios execution. However, scenarios were also tested
383 for different R(C) values. For example, Table 8 exhibits the results of executing scenario 11
384 when R(C)>0.75, 0.85 and 0.95. The total number of days that R(C)>0.75, 0.85 and 0.95 also
385 influences the total numbers of patients discharged during the simulation period. Red day
386 reduction per discharge was calculated as red days reduction compared to base case scenario
387 divided by total numbers of patients discharged. According to the result in Table 8, red day

388 reduction per discharge of scenario 11 is 0.2 which is higher than scenario 11-1 and 11-2. That
389 is to say, selecting R(C) > 0.85 for the condition maximises occupancy benefits for the least
390 disruption to patient care.

391 It must be recognized that a large amount of effort was made in HESMAD validation [13]. Also,
392 while some approaches can be easily achieved by the simulation model, similar approaches
393 would be challenging in the real world. For example, we can discharge patients early because
394 we know each patient's LOS in the simulation model, but we do not know their LOS in the real
395 world. However, it is important to keep in mind that the simulation study does not attempt to
396 propose exact mechanisms for hospitals. Rather, the simulation results demonstrate where
397 greater attention should be paid when addressing patient flow congestions within a hospital if
398 improvements are desired. In addition, due to the fact that the risk-free platform of simulation
399 model allows us to "repeat history" easily in the virtual environment or estimate what-if
400 assumptions, hence, it is an outstanding tool to support healthcare management decision making.

401 **5. Conclusion**

402 In conclusion, compared to analytical methods, this simulation model exhibits unsurmountable
403 advantages for understanding the possible effects of system change. The risk-free platform of
404 simulation model allows us to do pre-implementation evaluations, hence, it is an outstanding
405 tool to support hospital management decisions. This study tested the congestion prevention
406 method in the simulation model to investigate the potential impacts of different approaches on
407 hospital overcrowding. The expected outcome based on theoretical prediction of this method
408 was confirmed, that is, applying a less disruptive intervention is often enough, and more cost
409 effective, to reduce the risk level of hospital congestion. Making a small number of extra beds

410 available was a superior solution compared to discharging approaches to reduce crowding in
411 hospitals. In addition, the virtual implementation approach enabled testing of the method at a
412 more detailed level, thereby revealed some interesting findings difficult to achieve theoretically,
413 such as discharging extra two medical inpatients, rather than surgical inpatients, a day earlier
414 on days when R>R(C), would bring more benefits in terms of congestion reduction for the
415 hospital.

416 **Availability of data and materials**

417 The patient flow data used for developing the HESMAD model were obtained with approval
418 by the Ethics Committee, SA Health Office for the Research Study 'Congestion recovery and
419 optimisation of patient flows' (Application number 475.13). These data were used under license
420 for the current study, and so are not publicly available.

421 **Abbreviation**

422 **ED:** Emergency Department

423 **HESMAD:** Hospital Event Simulation Model: Arrivals to Discharge

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Authors' Contributions

WH carried out the simulation analyses, created figures and tables, and drafted the manuscript. SQ and CT collaborated with WH on developing the analytic plan, interpreting outputs, and developing the outline of the manuscript. All authors revised the paper critically and approved the final version.

Ethics declarations

Ethics approval and consent to participate

Not applicable

Consent for publication

Not applicable

Competing interests

The authors declare they have no competing interests.

498 **Supplementary Information**

499 Additional file 1: Reporting Guideline.

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