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Can a system dynamics model of the emergency department show which levers reduce bottlenecks and delays to improve access to care?

Sue McAvoy[1] | **Andrew Staib**[2,4] | **Gregory Treston**[3]

[1]Mater Misericordiae Ltd (Mater Medical Research Institute), University of Queensland Business School, Brisbane, Queensland, Australia

[2]Princess Alexandra Hospital, Brisbane, Queensland, Australia

[3]Mater Health Services, Mater Hospital Brisbane, South Brisbane, Queensland, Australia

[4]MRI-UQ, South Brisbane, Queensland, Australia

Correspondence
Sue McAvoy, University of Queensland Business School, St. Lucia, Queensland 4072, Australia.
Email: s.mcavoy@business.uq.edu.au

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Mater Misericordiae Ltd (Mater Medical Research Institute); The University of Queensland (University of Queensland Business School)

Abstract

The purpose of this paper is to demonstrate through practical application how a system dynamics (SD) patient flow model of an emergency department (ED) can show which levers effectively reduce backlogs to improve access to care. Overcrowded EDs are struggling to meet demand and access targets. In 2016 and 2017, in the UK and Australia, respectively, 15% and 28% of arrivals waited longer than the targeted 4-hr treatment time. Historically, simulation models that have informed access to emergency care have ignored the wider systems impacts. There is a growing awareness of the value of systems analysis tools for informing interventions and policy. In this study, we constructed a pilot system dynamics patient flow model, where the scope was the ambulatory and ambulance patient arrivals, the ED processes for acute and fast-track pathways, pathology and radiology services, the ED short-stay unit, and the Medical Assessment Planning Inpatient Unit. Patients queued to access constrained ED resources (doctors and beds) and diagnostic services (pathology and X-ray). The model was tested on actual data from five separate historical periods spanning 3 years. The resultant daily pattern of peaks and troughs in patient flow and system delays accurately replicated patterns in actual patient flows, resource use, and the location of delays. "What if" scenario analysis (b) simulated how access would have looked in the sample weeks with different intervention strategies, (b) simulated system limits on the basis of current resources, (c) accurately identified levers that historically have been most effective at minimizing ambulance ramping, and (d) identified when additional staffing would fail to improve flow.

KEYWORDS

emergency department, patient flow, simulation, system dynamics

1 | INTRODUCTION

1.1 | Background

McAvoy, Staib, and Birch (2018) identified a strong value proposition for the use of system dynamics (SD) as a tactical and strategic tool that could relax the assumption of ceteris paribus commonly used in traditional health models and in doing so contributes to the design of robust interventions capable of strengthening healthcare systems. Dynamic simulation models that map interdependencies at the systems level bring several potential benefits: (a) a more comprehensive understanding of the interdependence in the system and its implications for performance by those in the network and (b) a comprehensive view of the drivers that improve outcomes of costs and patient experience, whether they be optimized resourcing and data use, shortened wait times, more timely access to appropriate care, or the impact of intangibles such as the speed or quality of information (Reid, Compton, Grossman, & Fanjiang, 2005)

Institutionally, this century has been characterized by a strong call to promote the use of systems approaches and systems engineering tools to improve healthcare delivery (Calder et al., 2018; Caro, Briggs, Siebert, & Kuntz, 2012; Messina, 2017; Organisation for Economic Co-operation and Development, 2017; Reid et al., 2005; Research, 2009). A dynamic simulation model can provide system-level insights that help address the seemingly conflicting goals of healthcare to reduce per capita costs and improving the experience of care and the health of populations (Russell & Dawda, 2013). There is evidence of growth in the use of SD tools, particularly in the area of access to emergency care. Its uptake and use strategically has, however, been slow, and SD is infrequently the simulation method deployed leaving much room for further investigation, validation, and evidence-based trials (Mohiuddin et al., 2017; Paul, Reddy, & DeFlitch, 2010; Salmon, Rachuba, Briscoe, & Pitt, 2018).

The emergency care supply chain is characterized by many critical interrelated stakeholders whose decisions are largely made independently of each other. Decisions made in one part of the supply chain can have unintended consequences in other areas, and together they can have the collective systems effect of reducing access to and the efficiency of emergency care.

The demand for frontline emergency services (both ambulance services and emergency department [ED] services) is growing. In 2017 and 2018, ED admissions grew in Australia by 3.8% per year (Australian Government, 2017) nationally and by 9.5% in Queensland. Ambulance arrivals grew by 25.2% nationally and by 34% in Queensland. Emergency care in Australia costs in excess of 8 billion annually and improved access has been elusive.

A significant and sustained increase in acute demand, without a corresponding change to resources or policies, will put pressure on the EDs' capacity to treat patients in the targeted timeframe of 4 hr. Operational interventions recommended to manage increased arrivals so that patient outcomes are optimized and care targets are met will likely have wider implications including social and financial consequences. The authors believe there is a strong value proposition for a systems-level simulation tool that provides a virtual reality in which to explore the system-wide impact of proposed interventions.

For this study, a pilot SD model was designed and developed for the ED. The ED model design was based on the Mater Public Hospital Emergency Department. The development process used from problem conceptualization to scenario analysis and policy insight was the system dynamics development framework in Figure 1 (Sterman, 2000). Using an evidence-based approach, a series of realistic policy interventions (scenarios) were simulated, and their combined impact on system performance was recorded. The intent was to show how different strategies could have led to different outcomes in the sample weeks compared with the business as usual (BAU) case. Simulated outcomes also were evaluated against past evidence and clinical experience to evaluate efficacy and highlight assumptions in the model that may need rethinking in the next stage of this work.

1.2 | Goals beyond this investigation

Evidence-based decision making for access decisions in the ED can be regarded as a system behaviour. There is evidence in the Veteran Affairs Department in the United States that a participatory evidence-based SD approach involving models parameterized by live data feeds from care team metrics are able to (a) promote the reach of evidence-based decision making to drive better performance at the care team level, (b) foster a systems-level understanding of trends in healthcare service delivery, and (c) empower stakeholders to make locally optimized improvement policies for Veteran Affairs stakeholders in the United States (Lindsay Zimmerman, 2019; Lindsey Zimmerman et al., 2016). Hospitals are data-rich organizations that struggle to improve their performance in the face of increasing consumer demand. The simulation results from this pilot ED SD model suggest that it is a tool that could have strategic value to the clinicians and various care teams involved in the delivery of emergency care

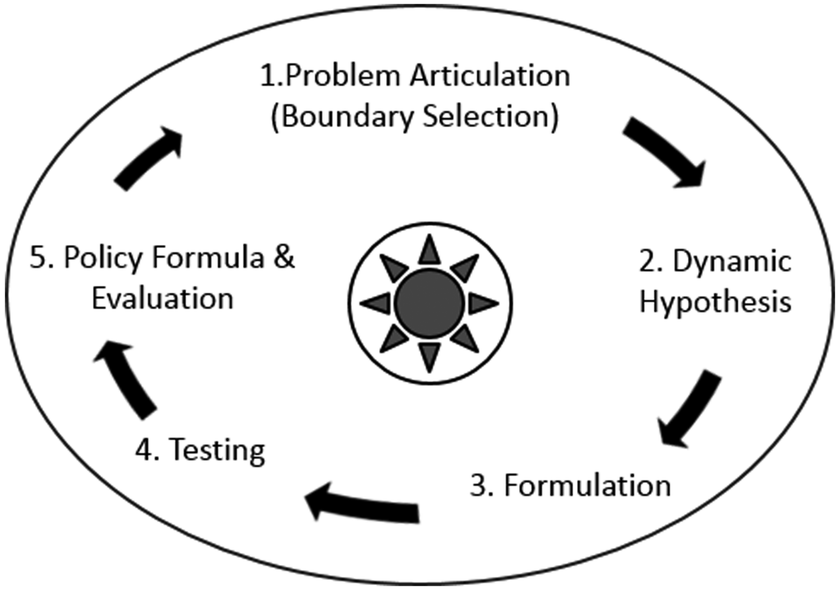

FIGURE 1 The modelling process (Sterman, 2000)

through "what if" insights informing decision making. SD models can provide a systemic view of the interactions of patients and ED processes, resources, units (departments), and information flows. It has long been suggested that these system-engineering tools, when designed for purpose, can optimize performance of the delivery of care (Reid et al., 2005). The goal of this research is to embed SD science into a hospital's data infrastructure. In a whole of system approach, the goal is for clinicians to interface with data scientists and data engineers to adapt and apply these tools to optimize access to emergency care. Data feeds that continuously parameterize the model will enable the SD intervention testing tool to utilize data to guide both the operational and strategic decisions that inform access to and the overall experience of emergency care for patients. Ongoing scenario analysis in this jurisdiction will provide informed insights into the impact on access to emergency care (efficiency, utilization, and cost) of an intervention as clinicians, care teams, and data specialists think analytically and collaboratively.

1.3 | Summary of systematic reviews of ED simulation modelling

We used a database search of simulation methods applied to the ED to emphasize that only a very limited number of studies have applied system dynamics. This established a rationale for undertaking further SD research. We searched Scopus for systematic reviews investigating the application of computer simulation methods to scrutinize patient flow through the ED. We included the following range of search phrases: ED, emergency, accident and emergency, computer simulation modelling, computer and simulation or simulation or discrete event simulation (DES) or SD or agent-based modelling, and systematic review or systematic reviews or literature reviews. We restricted the search to English language and searched from 2010 to current.

Out of the 225 references identified, three systematic reviews of the use of computer simulation modelling methods for understanding the dynamics of flow in EDs were identified (Mohiuddin et al., 2017; Paul et al., 2010; Salmon et al., 2018). Paul et al. (2010) presented a review of ED simulations literature from 1970 to 2006 with the goal of highlighting how simulation studies can enhance understanding of overcrowding in ED's and as a tool can potentially help inform solutions. Although most studies utilized DES, SD did make an appearance. Mohiuddin et al. (2017) systematically reviewed the peer-reviewed literature to investigate the use of computer simulation for understanding the causes of overcrowding in the ED under the jurisdiction of the UK National Health Service. Their review yielded 21 studies (published either in peer-reviewed journals or as full conference papers) between 2000 and 2013 that met their inclusion criteria. They found that 10% of simulations used SD modelling. Salmon et al. (2018) reviewed simulation modelling applied to ED's focusing on all English language papers from 2000 to September 2016. Of 254 relevant publications, 209 papers employed DES, only 18 (7.1%) used SD, and a further 13 (5.1%) used a combination of either DES/agent-based modelling or DES/SD.

This relatively low base for studies exploring the value of SD methodologies in healthcare service delivery has motivated this application of SD to emergency care access.

2 | METHODS

2.1 | Modelling process steps

The objective was to investigate whether evidence-based system dynamics tools can inform healthcare service delivery strategy, specifically access to emergency care. Built on an aggregate patient flow architecture specific to the ED being studied, SD is a method focusing on the "big picture" and can be used to understand the feedback mechanisms within the ED and its related departments and their influence on both system behaviour and system efficiency over time.

Timely access to emergency care is a widely acknowledged problem and the focus of this study. The iterative modelling process steps, beginning with problem articulation, are outlined in Figure 1 below.

2.2 | Qualitative system description

An ED in a multifunctional tertiary hospital has a unique yet complex identity. Its dual role is to provide both fast, high-level frontline emergency care, and a sorting function for inpatient admissions while maintaining a capacity to respond to unplanned medical emergencies. All EDs are complex systems operating with planning uncertainties and they are themselves embedded in bigger more complex social systems. In Figure 2, Staib et al. (2017) present the process and governance architecture that defines the ED-inpatient operating system in a typical Australian hospital. For this pilot SD study, the model boundary will exclude the prehospital clinical processes and ward activity not related to the short-stay or medical assessment planning units. As indicated by the identified boundary marker in Figure 2, the model will incorporate all process measures of overcrowding identified while recognizing that arrivals, both ambulance and walk-in, are exogenous. Acute beds, short-stay beds (boarding), and ramping will be stocks, and the model will calculate average residency time.

The ED for this study is dual stream with higher acuity patients processed on an acute pathway and lower acuity patients taking a fast-track (FT) pathway, with the FT pathway characteristically operating more like a primary care facility than a hospital ward. Acuity refers to the severity of the patient's illness or injury, and it is used during triage to determine the patient's treatment pathway. Both pathways are open 24 hr a day 7 days a week. A conceptualization workshop, numerous hospital site visits, historical behaviour over time data from the Emergency Department Information System (EDIS),[1] pathology and imaging departments along with staff rosters, and regular interviews with key stakeholders from related units and departments (including clinicians, nurses, business managers, ward managers, Queensland Ambulance Service, data and analytics providers, and diagnostic teams) enabled the development of rich pictures.

A causal loop diagram (CLD) was then developed, and a map of the interdependencies between system components was produced. ED's in other jurisdictions informed the conceptualization processes to ensure expansive thinking (a preparedness to consider widely and be challenged) in mental model construction. Figure 3 below captures the content of the rich picture developed.

From this rich picture, a simple CLD was surfaced. The CLD (Figure 4) highlights the dominance of balancing loops that operate to ensure an ED can flow patients without serious backlogs.

When flow through the ED is impeded and acute beds fail to empty, a reinforcing effect of multiple backlogs can cause sustained ambulance ramping (patients remain on stretchers, waiting to be moved into acute beds).

This model scope focused on the ED at the process level to

1. Make transparent the relationship between resources and patient flow rates.
2. Quantify the causation, magnitude, and consequences of actual delays.
3. Provide insights into acute and short-stay bed occupancy and system limits as demand for emergency admission increases.
4. Provide insights into the efficacy of proposed interventions to improve access to care.

Highlight where bottlenecks might occur with an increase in throughput and what their quantum might be.

Figure 5 represents the wider hospital system and process flow in which the ED is embedded. Some capacity and resource blocks are identified to highlight the interdependencies both within the ED and amongst departments.

Figure 6 represents the dynamic hypothesis (boundary). Each box represents a subsector of the stock and flow model that was developed. The model architecture replicated the major elements of the ED processes,

[1]Pearce, R

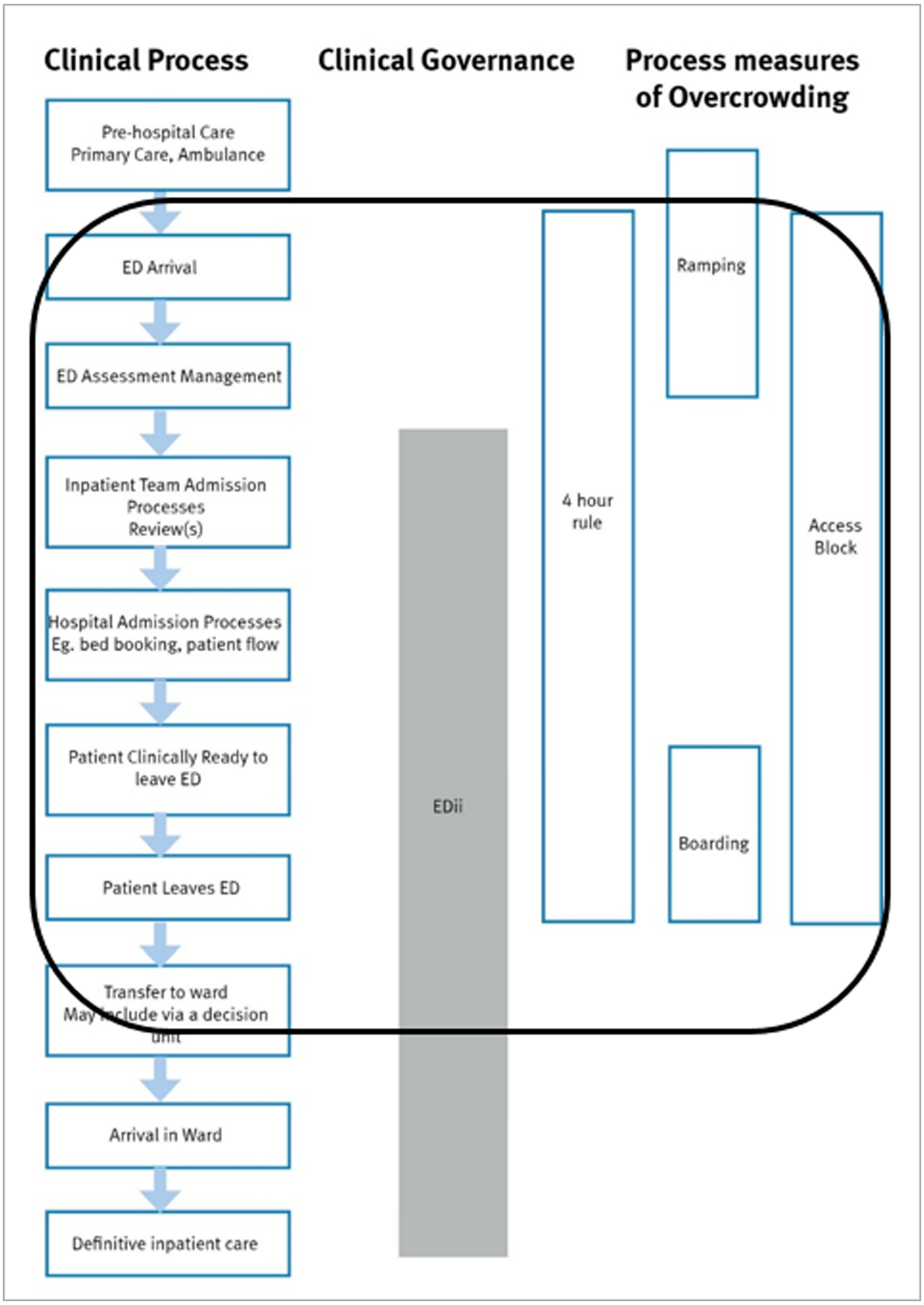

FIGURE 2 Emergency department (ED)-inpatient interface (EDii) and pilot model boundary [Colour figure can be viewed at wileyonlinelibrary.com]

pathology and radiology services, the ED short-stay unit, and the Medical Assessment Planning Inpatient Unit. Some of the interdependencies have been represented using arrows.

2.3 | Quantitative model development

The rich picture, CLD, and conceptual map informed the simulation model developed in Sysdea[2] using the agile strategy dynamics method (Warren, 2015). The developed model flowed patients (arriving exogenously) through a series of stations beginning with registration where patients could experience delays waiting to be triaged. Subsequent delays potentially involved waiting for an ED treatment bed/space, waiting to see a doctor, undergoing assessment and management, waiting for diagnostics, waiting for results, waiting for inpatient admission, and awaiting discharge. In the model, the decision rule for registration and triage was a first-in first-out basis, although in reality, very high-acuity (scale of seriousness) cases would take precedence over arrival order. Although

[2]Strategy Dynamics Ltd

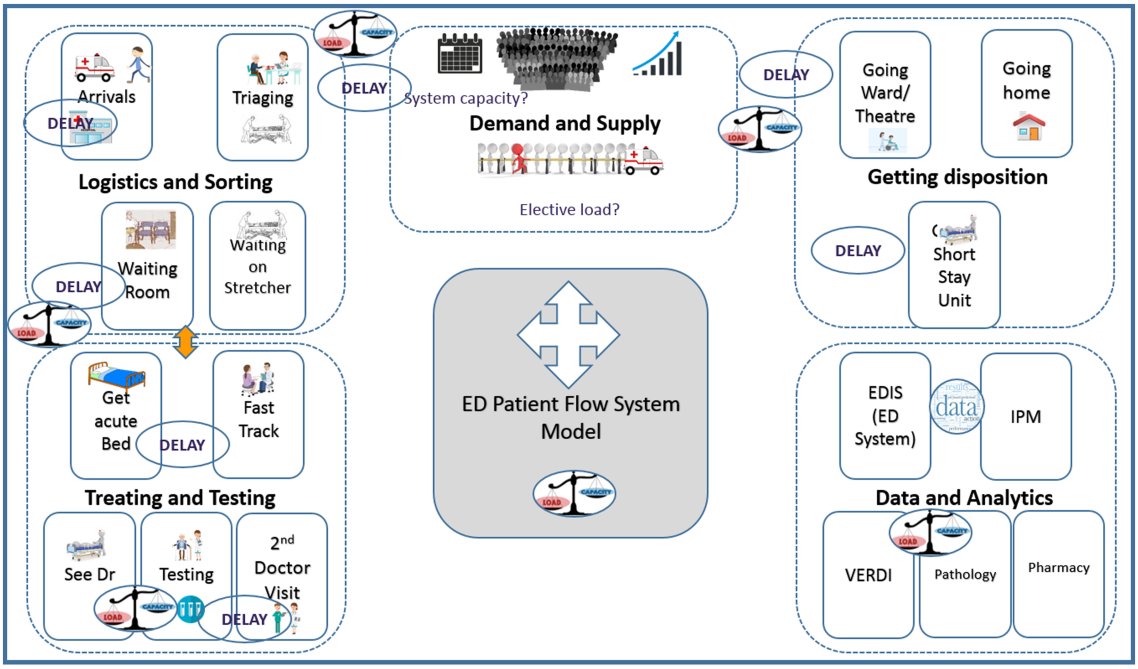

FIGURE 3 *Rich* picture *of* access *to* emergency department (*ED*) care [Colour figure can be viewed at wileyonlinelibrary.com]

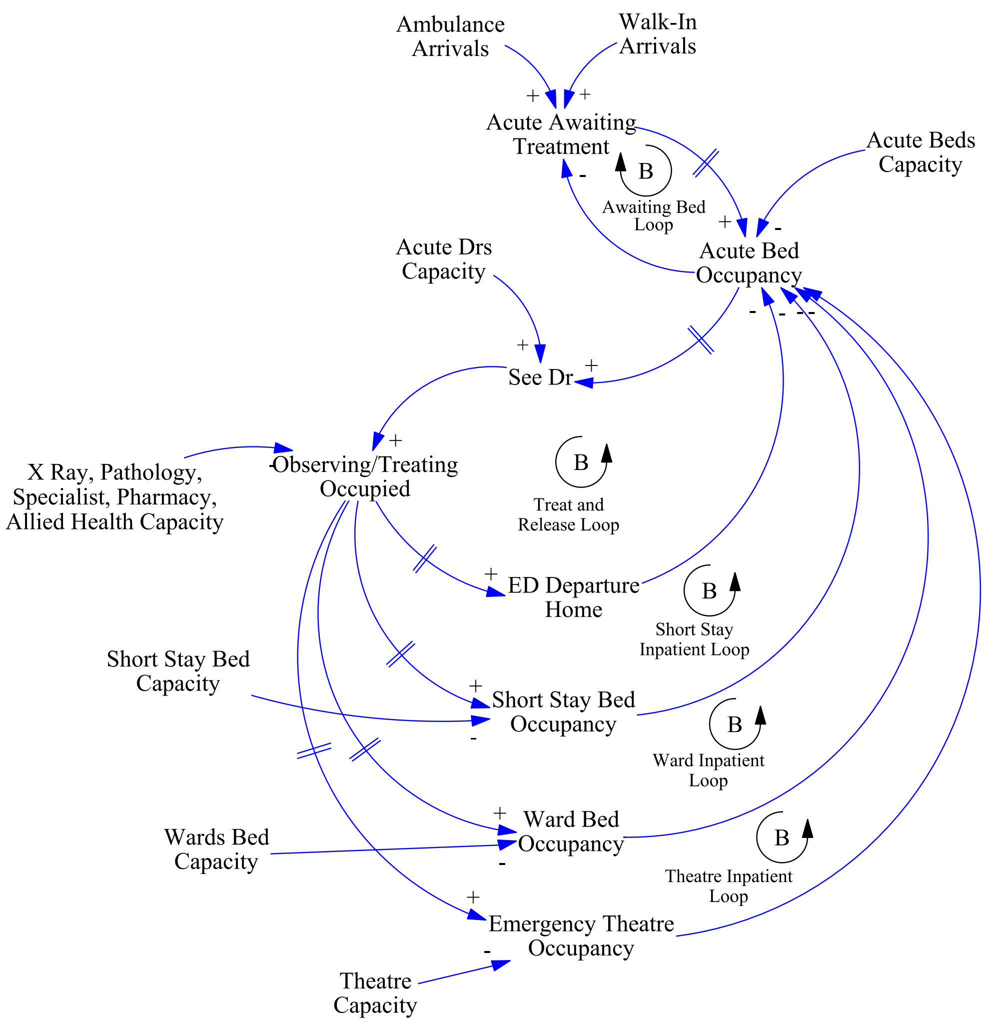

FIGURE 4 Causal loop diagram of the emergency department (ED) (McAvoy, Staib & Birch, 2018) [Colour figure can be viewed at wileyonlinelibrary.com]

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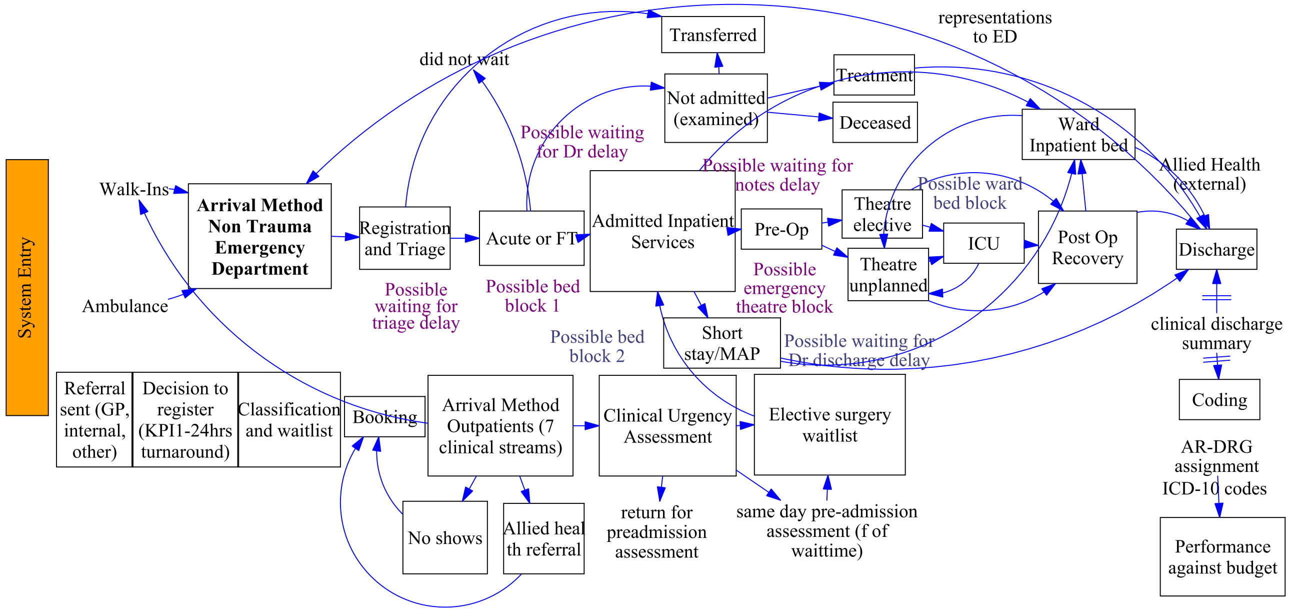


FIGURE 5 System flow and interdependencies. General practitioner (GP), key performance indicator (KPI), fast-track pathway (FT), intensive care unit (ICU), Australian Refined Diagnostic Related Groups (AR-DRG), International Classification of Disease (ICD), Short-stay and Medical Assessment and Planning (MAPU) units [Colour figure can be viewed at wileyonlinelibrary.com]

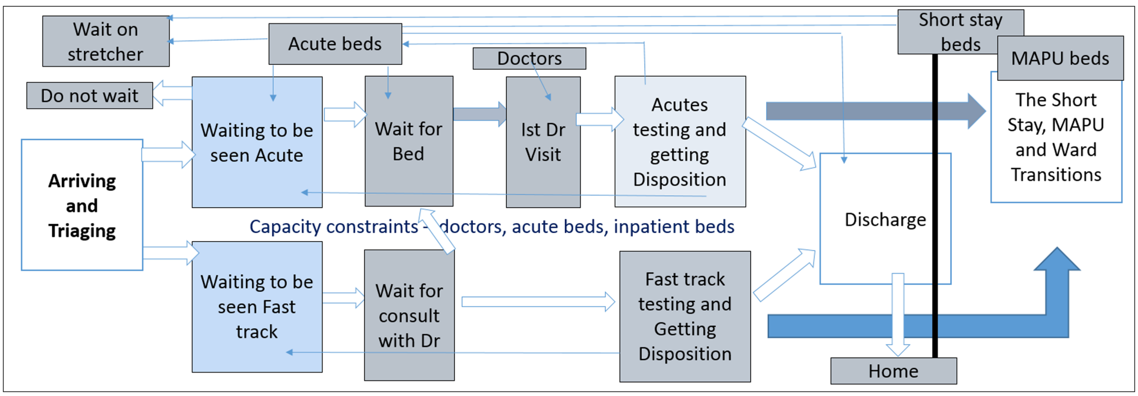


FIGURE 6 Sectors in the stock and flow model [Colour figure can be viewed at wileyonlinelibrary.com]

this is a limitation of the model, there is a rationale for the choice. The ED informing this model is not a trauma ED, meaning it receives a low number of the highest acuity patients likely to jump the queue. Further, the time journey and delays built into the model accurately reflect the average time journeys of all. A more nuanced triaging of acute patients will be a focus of future iterations of the model.

Patients progress through the ED when resources are available, so flow is constrained by resource availability in the model. For acute patients, this means the availability of an acute ED treatment space. For FT patients, who typically have a lower acuity ranking, there must be an available space in a consultation room or the FT waiting room. Patients were generally of two types: those who became inpatients and those who were treated, stabilized, and discharged. Patients who were transferred were excluded from this study because the volume was very low; however, they will be included in future iterations of the model to ensure wider application. Patients leaving before or during treatment exit the model at triage, although realistically their exit could occur at other times. This pilot model assumed patients have standard imaging and pathology tests, each with a test duration of 15 min for the actual procedure. Some, but not many FT patients, also had one or both types of investigations. Diagnostic testing was mapped as a flow to imaging, pathology, or imaging and pathology wherein patients queued for one and then the other so in reality, testing may take a lot longer depending on demand.

Acute patients do not free up a bed when they have tests. FT patients may move from the consultation room to the waiting room while undergoing treatment so the model reflects this logic. Some delays occurred concurrently such as waiting for a bed allocation and waiting for papers to move to a ward. For patients who arrived by ambulance, arrival time on the EDIS was the time the patient is triaged. There are a finite number of acute beds. It is the series of balancing loops identified in the CLD that enable the acute beds to become available to new arrivals. No availability means no flow or bed block. This contributes to ramping (patients remaining on stretchers).

To develop the model and establish a base case, real historical time series data for five separate weeks were used. The logic behind the weeks sampled was to capture seasonality impacts from different times of the year and also enabling comparison by ensuring one of the weeks was consistent across all 3 years. Synchronized random variables are used to direct and distribute patients on pathways. Service times at the various activities are not stochastic. A fixed unit of time derived from historical patterning data, institutional information, and clinical experience has been used to estimate treatment times. After seeing the doctor, patients queue to begin diagnostic processes for which standard testing times are used. It is possible to vary all timing assumptions in the simulations. Future model developments will address the variation in type and timing of possible tests.

A doctor's roster determines the numbers of consultants, senior medical officers, registrars, and residents on duty at any one time. The acute and FT pathways are separately resourced. Even though the staff may flex between pathways to meet demand, this has not been considered in this first iteration of the model. The model runs for 7 days. Those patients in the system at midnight are accounted for in the model so initial conditions accurately represent the sample weeks. The chosen time step (dt), 15 min, reflects the estimated duration of a first consultation with the doctor.

The acute bed (Figure 7) and triaging (Figure 8) subsectors of the simulation model are pictured below. The acute bed subsector manages the flow into the *get acute bed* stock via a submodel structure in the *wait for bed* sector of the model. This is visualized in Figure 6. A patient needs to be waiting and a bed needs to be available to flow. Beds vacate on the basis of the formula in the vacating beds flow: "actually filling SS bed" + "into Mapp" + "Direct to wards" + "discharging." In this simulation shown, five acute beds were occupied at midnight out of the 16 possible beds, leaving 11 vacant. Converters represent this part of the system, and the connectors show how elements affect one another. The numbers appearing in the flows represent base-case patient flow versus a scenario for one time step. Figure 7 manages the vacant beds accumulation that informs the flow to "get acute bed." The vacant and occupied beds stock shows actual historical data against simulated data. The triaging subsector (Figure 8) assigns flow to either an acute or a FT treatment pathway. There is a typical number of patients triaged per time unit of 15 min on the basis of behaviour over time data, however, given the uncertainty of condition on presentation, this can be varied along with the number of nurses assigned to triage patients. Triaged patients move into waiting stocks, which are effectively waiting rooms, and they accumulate there until there is capacity to flow. Here, the interdependencies within the system determine flow, such as the feedback between short-stay bed availability and the flow from an acute bed to the short-stay unit. Patients who leave the system, called do not waits, are removed at triage in this model. Future versions of this model will represent these flows

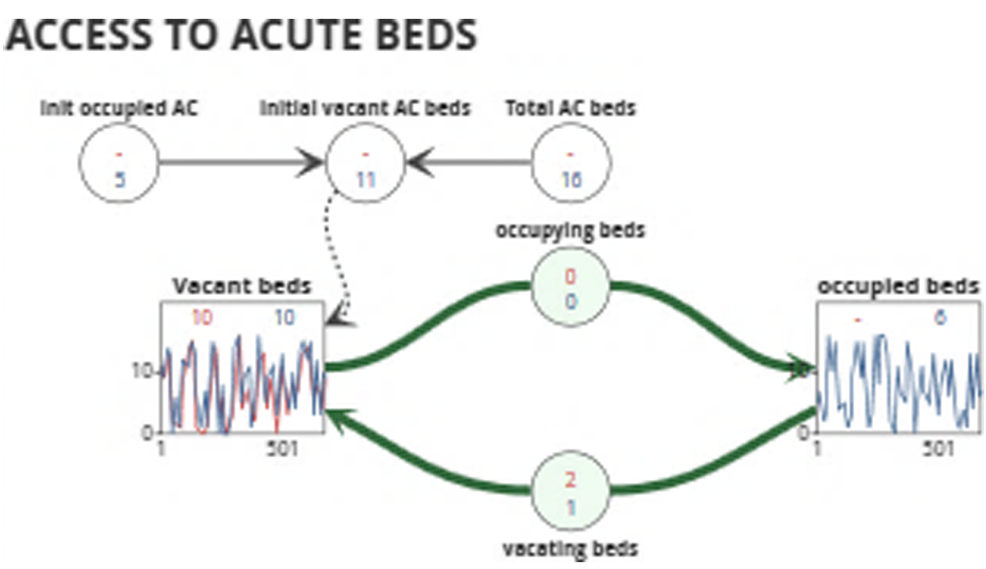


FIGURE 7 Acute beds subsector [Colour figure can be viewed at wileyonlinelibrary.com]

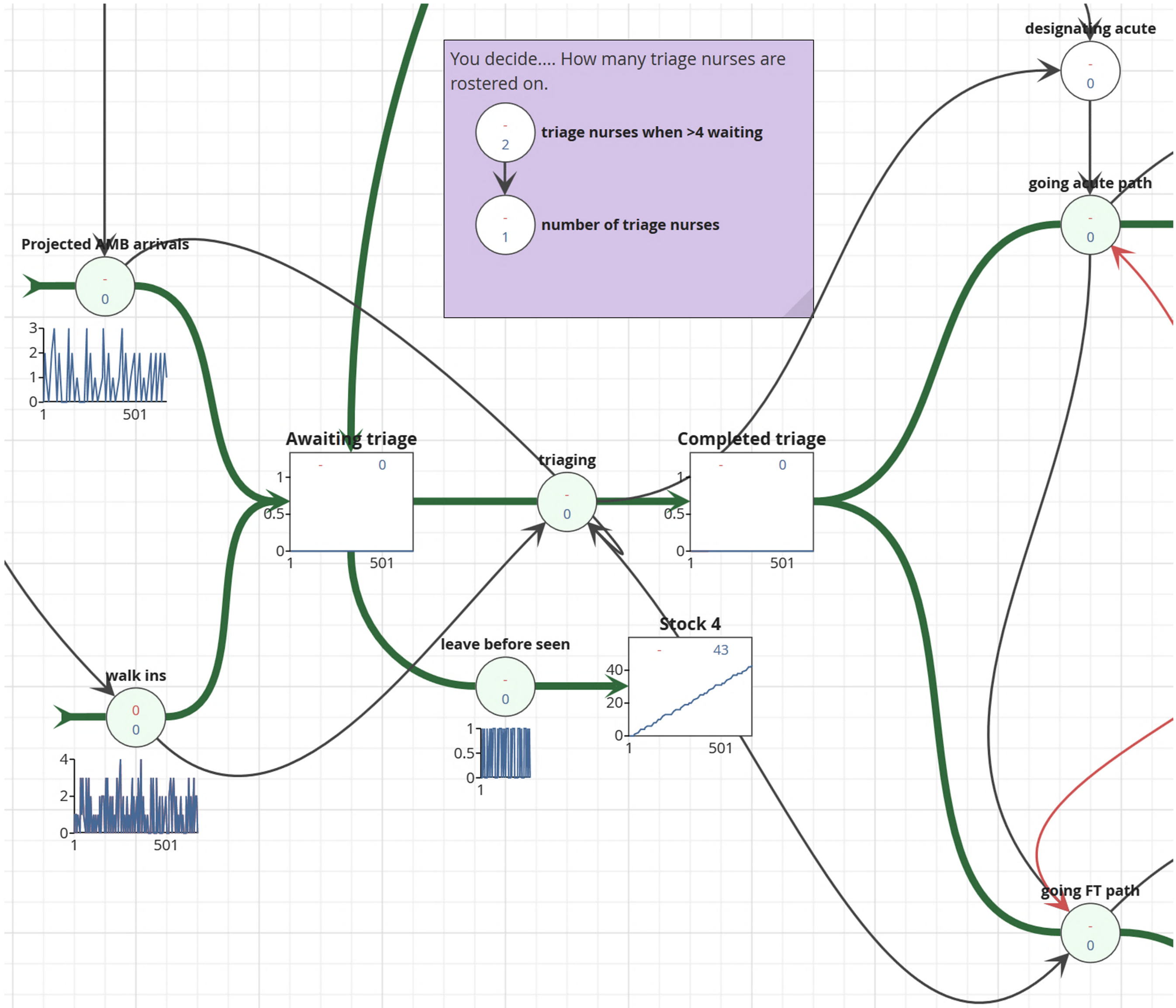


FIGURE 8 Triaging subsector [Colour figure can be viewed at wileyonlinelibrary.com]

more accurately by differentiating between those leaving before and after treatment commences.

2.4 | Data, model assumptions, and validation

The model was informed by anonymous patient-level flow data collected from EDIS for five full 7-day week periods covering Monday 00:00 through to Sunday 23:59 for the weeks of February 6, 2017 (summer), October 2, 2017 (spring), February 5, 2018 (summer), February 3, 2019 (summer), and June 9, 2019 (winter). The model was initially constructed using February 2017 behaviour over time data to establish a base case. However, as actual data can be sketched into all variables, the model was run for each of the 5 weeks data were collected to ensure the model output was credible. Validity tests included conservation tests, a reasonably good pattern match between simulated outputs and actual data, rigour under extreme tests (e.g., no negative stocks), and acceptable and logical outcomes from sensitivity testing.

Patient-level data for the reference mode/model construction and incorporated delays and volumes included (a) assigned triage category, (b) arrival mode, (c) arrival time, (d) triage date and start time, (e) triage end time, (f) time doctor seen, (g) total length of stay, (h) first location, (i) time to admission request, (j) time to ward ready, (k) time from admit request to ED discharge, (l) actual ED discharge time, and (m) disposition pathways. Resource capacity and utilization data were available for acute and short-stay unit beds for all time sets as were data for patients in the system at midnight. One full day's worth of actual pathology and imaging flow data were constructed to inform the time delays and distributions in the model.

Because the flow onto wards is not connected to actual ward capacities in the pilot model and the flow out of the short-stay unit is not completely under the control of the ED, it was necessary to calibrate a delay variable to control the outflow from the short-stay variable in the model. The variable was calibrated to reflect the actual vacating of short-stay beds and for each time period, it is slightly different. The logic is that this variable reflects the processes and resource interdependencies governing the flow for that period. Significantly but not surprisingly, flow correlated well with short-stay unit doctors on roster. A fully specified variable will be designed into subsequent iterations of the model.

The model construction and parameterization was based on the assumptions and data sources in Table 1. Most assumptions are decisions which can be changed in the model.

2.5 | "What if" scenarios

As this is a pilot model, and the purpose of this paper is to demonstrate through practical application that a system-level analysis tool can identify levers for change, a small number of plausible intervention scenarios have been identified for testing. The scenario focus is the acute treatment pathway.

The scenarios are explained in Table 2. Although some of the results compare outputs across weeks to explain model performance, where scenarios are compared, June 2019 has been selected as the BAU week. The impact factors measured (as proxies for flow) are *impact on acute bed vacancy* and *ramping* (patient waits on stretcher). One weakness in ramping as an impact factor is that it does not show how long an ambulance ramped.

2.6 | Sensitivity analysis

The times allocated to key processes (seeing doctor and testing) were identified as input parameters containing uncertainty. Uncertainty is also introduced by assuming a replication of historical arrival patterns. To ensure model robustness, we performed the following sensitivity analyses:

- Time seeing doctor and testing times increased by 50% and 75%.
- A Poisson distribution was used to randomly arrive all patients.
- No delay versus a calibrated delay for exiting acute.
- Increasing percentages designating acute by 10%.

In all instances, outputs increased and decreased as would be expected. No stock ever went negative. A 50% and 75% increase, respectively, in time spent seeing the doctor for the first time and in undergoing testing impacted the acute awaiting treatment stock as expected. Figure 9 shows that there is an expected increase in people hours waiting as the doctor consultation time per patient increases. As treatment time increases, the impact will be felt most at the periods of peak utilization of facilities, which corresponds with the peak in arrivals. If the periods most affected by a longer doctor consultation are matched against the vacant acute beds, it can be inferred that this impact is most felt during times of peak bed utilization, which makes sense. The conclusion here is that adding extra doctors would be beneficial at these times but may have less impact at other times.

3 | RESULTS

Five separate historical weeks were simulated against actual data. Simulated patient time journeys in acute ED treatment spaces successfully replicated historical residency patterns for patient stay in the ED. Capacity constraints and delays built into the flow formulas accurately created delays and bed blocks so that simulated bed use patterns reasonably reflected actual bed use patterns as evident in Figures 10, 11, and 12.

R^2 results comparing the simulation output with the actual historical data for acute bed vacancies in Table 3 suggest a reasonably good correspondence between the actual data and the simulated output. This suggests that if alternate interventions are tested in the model, the material and information delays in those weeks are reasonably well represented, and therefore, the simulated outputs would provide reliable insights into the likely impact of the intervention on flow.

The lower R^2 for February 2018 is in part due to the model diverging from actual at midnight on Monday evening until lunchtime Tuesday. At this time, the short-stay beds were not blocking the flow. What happened was that the acute beds, in the early hours of Tuesday morning, were full with Monday's late acute arrivals. Abnormally, 16 acute beds were full at midnight on February 5, which is an outcome the model has not and could not predict. Coinciding with this utilization of capacity in acute was a lower number of acute doctors on roster as is normal at midnight.

TABLE 1 Model assumptions and formulas

Process/resource	Data source	Assumptions
Arrivals by type	EDIS	Triage and treatment progression is FIFO. The historical weekly ambulance arrival patterns are a good indicator of future weekly ambulance arrival patterns, but the model can run a number of selected cases. The flows for "what if" scenarios against base case is formula: "future amb presents/day "and "future walk-ins." A select case condition has been used to construct alternate arrival scenarios for testing
Main waiting room		No limit on capacity has been assumed
Triaging	EDIS	Maximum of 4 per 15 min. Formula: min("Awaiting triage", 4)
DNW (leave before seen)	EDIS	A percentage of both acute and FT patients do not wait for treatment and exit model at triage. Formula: if "Projected AMB arrivals" +"walk ins" > 0 then pulse(1, 26, 12) else 0
Proportion designating acute (by triage category)	EDIS	A variable percent of patients presenting to emergency department designate acute; the remainder designate fast-track (after DNW's) Formula: if "RND no. generator 1" ≤"% designating acute" then "triaging" else 0; and "triaging"-"going acute path" for fast track.
Waiting to be seen	EDIS	People waiting to be seen only flow when an acute bed or consult room is available. See below
Acute beds	EDIS	16 acute beds. Occupation is not dependent on a doctor being available. Formula: min("Acute awaiting treatment","Vacant beds")
FT consulting spaces	EDIS	Three consulting spaces, a plaster room, and a procedure room
See first doctor and time with first doctor	EDIS and expert opinion	Formula: min("Available doctors", "1st doctor await") 15 min has been used as the base case first visit duration as reflected in the flow to testing
Testing	Verdi[a]	One test can be performed every period and patients enter a FIFO queue. Longer tests have not been considered at this stage. Historical percentages inform quantity flowing. There is a no-test pathway. With faster flow, the same testing decision is ensured as patients are distributed from a waiting stock. Testing only begins after the first doctor visit. For

(Continues)

TABLE 1 (Continued)

Process/resource	Data source	Assumptions
		example, need X-ray formula: Delay ("seeing Dr one in batch",1)*"next patient Xray?" + delay("seeing dr 2 in batch",1)*"Overflow 1 xray" + delay ("seeing Dr 3 in batch",1)*"overflow 2 xray" + delay("seeing Dr 4 in batch",1)*"overflow 3 xray" + delay ("seeing Dr 5 in batch",1)*"overflow 4 xray"
Proportion designating fast track (by triage category)	EDIS	Those that do not designate acute designate FT. Patients can move from consulting rooms to the waiting area to await tests and results
Doctors by type (consultant, registrar/senior health officer/resident)	Rosters	Assumes that doctors do not flex between acute and FT paths. Model assumes patients see the doctor twice, once after testing. Extra testing that may occur has been factored into disposition delays informed by behaviour over time data
Specialists and allied health	EDIS	Contribute to delays indicated by data but not identified explicitly in this pilot model.
Nursing and other nonmedical staff		Not explicitly used to constrain flow but inherently factored into specified delays.
Disposition pathways and proportions	EDIS and iPM	Short stay, medical admissions unit, wards, and discharge to home follow typical repeatable patterns and delays informed by behaviour over time patterns
SSU and MAPU beds	EDIS and iPM[b]	A significant number of acute patients and some FT patients flow to constrained SSU/MAPU beds and from there to a ward, SSU/MAPU or home. E.g. SSU allocations formula: min("allocated SSU", "SSU beds vacant")
Wards	iPM	Some patients flow direct to wards. The wards are not constrained in this pilot model. Note: Flow to wards is not capacity driven in this pilot; function of variable delay
Leaving SSU	EDIS	This involves both a fixed and variable delay—variable derived from calibration to match historical SSU bed vacancy pattern. Formula: If "Tier 1 ED Short Stay" > 0 then Delay("actually filling SS bed" + "AED FT to SS"-"SS to wards"-"SS to MAPU","SSU fixed delay") + "SSU home in system at midnight" else 0

(Continues)

TABLE 1 (Continued)

Process/resource	Data source	Assumptions
QAS ramping	EDIS	Ambulances will ramp when acute beds are vacant <1 and/or < 1 bed in a previous period. Formula: If "Vacant beds" ≤ "Trigger ramping if vacant beds ≤" or "Vacant beds delayed" ≤ "Trigger ramping if vacant beds ≤" then 1 else 0
Readmission	EDIS	Not specifically considered for this pilot model

Abbreviations: AED-FT to SS, fast track patients to short-stay unit; AMB, ambulance; DNW, do not wait; EDIS, Emergency Department Information System; FIFO, first in first out; FT, fast track; MAPU, Medical Assessment Planning Inpatient Unit; QAS, Queensland Ambulance Service; RND, random; SSU, short-stay unit.
[a]IP Health
[b]ISOFT

TABLE 2 Model "what if" scenarios

Scenario No.	Description
1	Addition of two extra acute beds
2	Addition of three extra SSU beds (no other change)
3	Addition of two extra acute and three SSU beds and extra doctor daily (except Saturday)
4	Addition of an extra doctor daily except Saturday
5	Addition of an extra doctor daily (except Saturday) and an extra acute bed
6	Impact of 10% growth in acute flow (no interventions)

Abbreviation: SSU, short-stay unit.

The model simulations run against base case are useful for wider insights. When the simulation diverges from the actual, it encourages a deeper inspection of the dynamics that in turn provides a more comprehensive understanding of process drivers and events. Figure 13 shows the value of this analysis in interrogating the patterns and trends. For example, the left-hand circle highlights the model's current inability to factor in the differing acuity of patients in the system at midnight meaning, in this case, the model processes the patients faster than occurred. The middle circle shows the model sends patients home faster than occurred on Friday morning. This coincides with a shift changeover, which could slow discharge. The circle on the right highlights filled acute beds early Sunday morning, which is not a normal pattern. The actual data also suggest that the model is underestimating the time patients remain in an acute bed on Friday evening and early Saturday morning. Both may be explained by demand arising from Brisbane's weekend party culture. This deeper dive into behaviour informs a more nuanced understanding and supports both dynamic thinking and system as a cause thinking (Richmond, 1993).

The acute and short-stay unit beds are part of a feedback loop. Around 50% of acute patients flow onto a short-stay bed so for the patient to flow, the short-stay bed must be vacant. To accurately model patient flows, both areas of the model must replicate actual trends. In order to ensure the simulated patient flows out of short-stay beds matched the trends in the real data, a calibrated delay reflecting the short-stay processes and procedure was constructed. The results in Figure 14 for June 2019 show that the calibrated delay, which enables a patient to

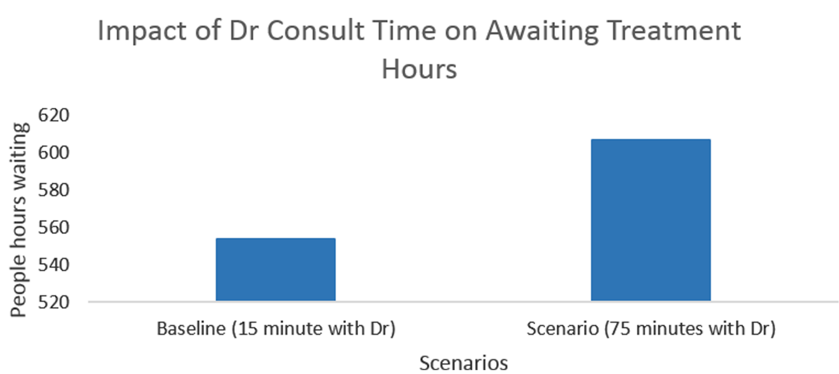


FIGURE 9 Impact of doctor consult time change [Colour figure can be viewed at wileyonlinelibrary.com]

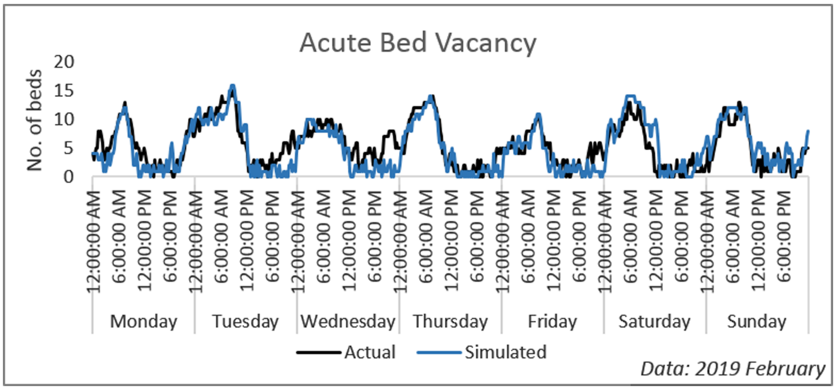


FIGURE 10 Acute bed vacancy, February 2019 [Colour figure can be viewed at wileyonlinelibrary.com]

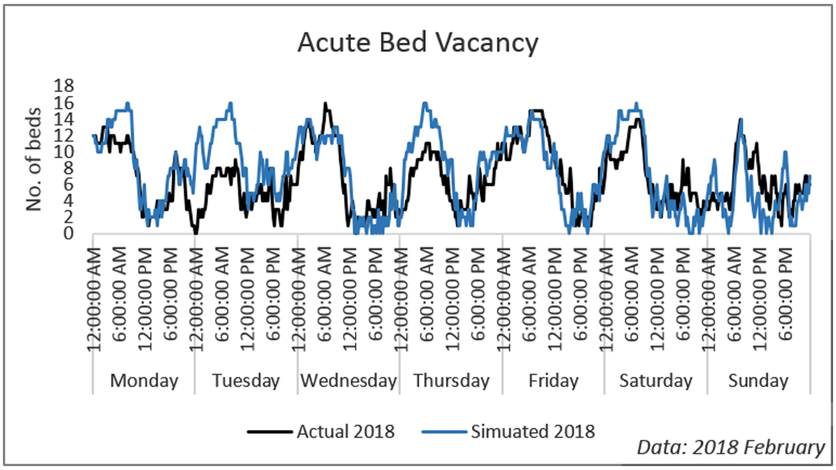


FIGURE 11 Acute bed vacancy, February 2018 [Colour figure can be viewed at wileyonlinelibrary.com]

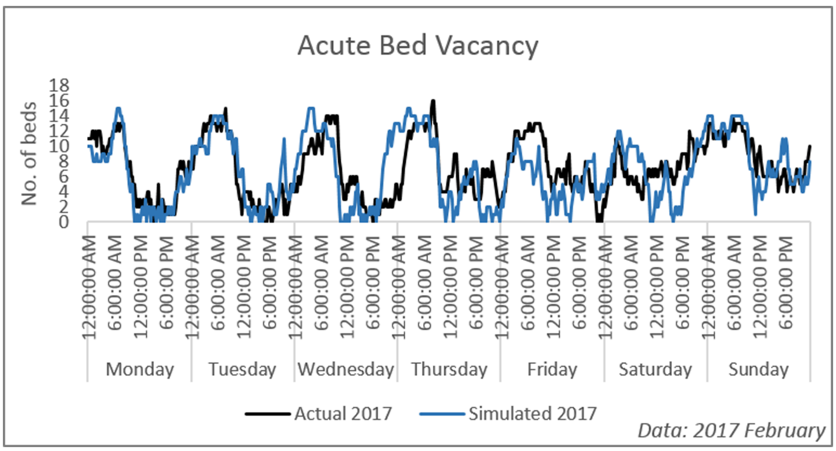


FIGURE 12 Acute bed vacancy, February 2017 [Colour figure can be viewed at wileyonlinelibrary.com]

TABLE 3 R^2 of actual versus simulated acute beds

Model	February 2017	February 2018	February 2019
Ambulance arrivals per week	329	357	443
Walk-ins per week	537	527	558
Designate acute	446	442	510
Initialization of acute beds (full)	5	4	14
R^2 simulated acute beds versus actual	.665	.54	.696

flow out of short-stay, roughly correlates with the times the short stay has doctors rostered on. Patients, however, do still flow from the short-stay unit in the absence of doctors specifically rostered on in the unit. It should be noted that it was harder to simulate the short-stay bed movements. There are a number of factors that contribute to this complexity. Short-stay unit is effectively an inpatient ward with flows likely to be more heavily impacted by ward and specialist doctor dynamics. Besides, the short-stay exhibits "daylight hours processing" whereby elderly patients when ready for discharge will not be discharged at 0200 h but rather will be

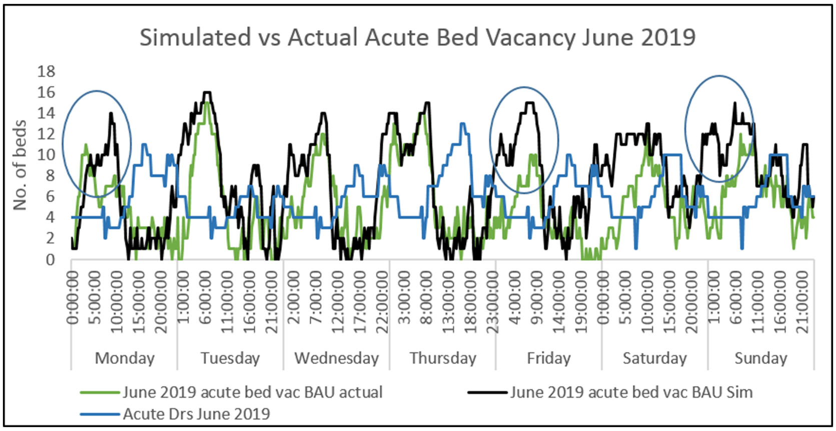


FIGURE 13 Acute bed dynamics with doctors, June 2019 [Colour figure can be viewed at wileyonlinelibrary.com]

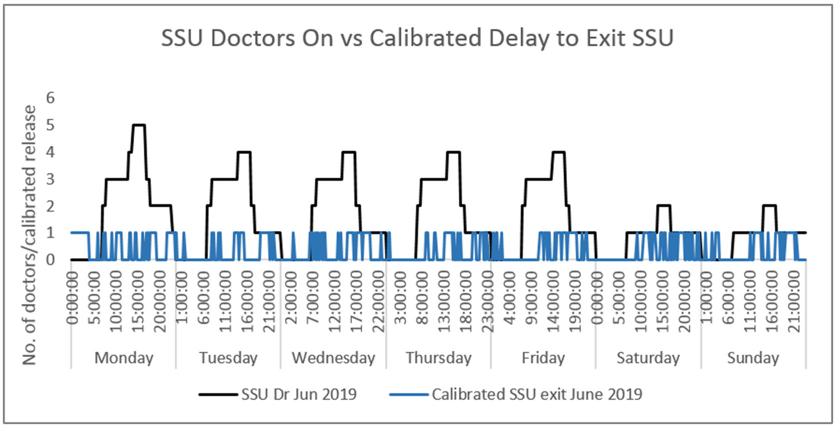


FIGURE 14 Calibrated exit variable versus short-stay unit doctors [Colour figure can be viewed at wileyonlinelibrary.com]

discharged at 0800 h on the basis of realistic sociocultural consideration.

Several parameters in the model needed to be changed to accurately represent the conditions of the respective weeks as distinct from the February 2017 week. Changes included the inflow of patients, the state of the system at midnight, the doctor's rosters, and the calibrated delay for the short-stay unit, which in each instance aligned reasonably well to the short-stay doctor's rostered on. Figure 15 below is a visual of June 2019 actual versus simulated short-stay bed vacancies.

To provide a practical application of the value of the SD model, the scenarios tested have been limited to two impacts: impact on acute bed vacancy and impact on ramping. Future work will extend these impact factors. The scenario outputs are compared with the historical June 2019 data set and the simulated data under BAU. Some of the scenarios that were explored show less pressure on acute beds (Figures 16 and 17).

Figure 18 compares ramping under all relevant scenarios. Scenario 6 adds 10% to flow through acute, which has a strong impact on ramping as would be expected.

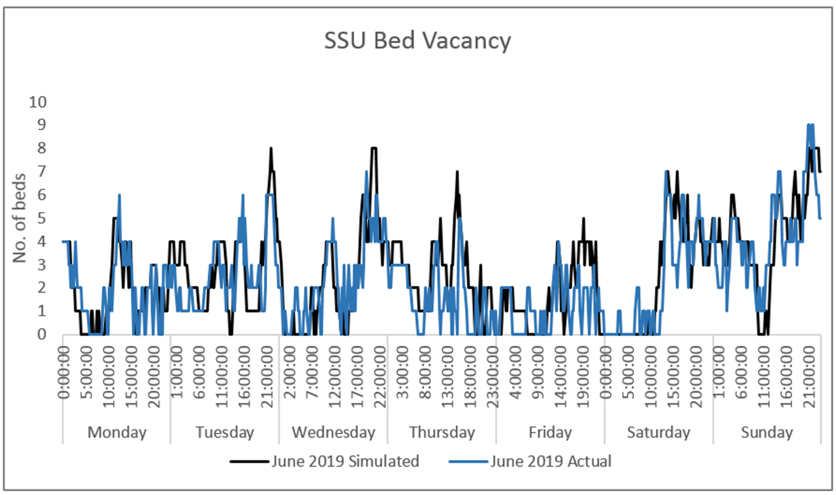


FIGURE 15 Short-stay unit bed vacancy [Colour figure can be viewed at wileyonlinelibrary.com]

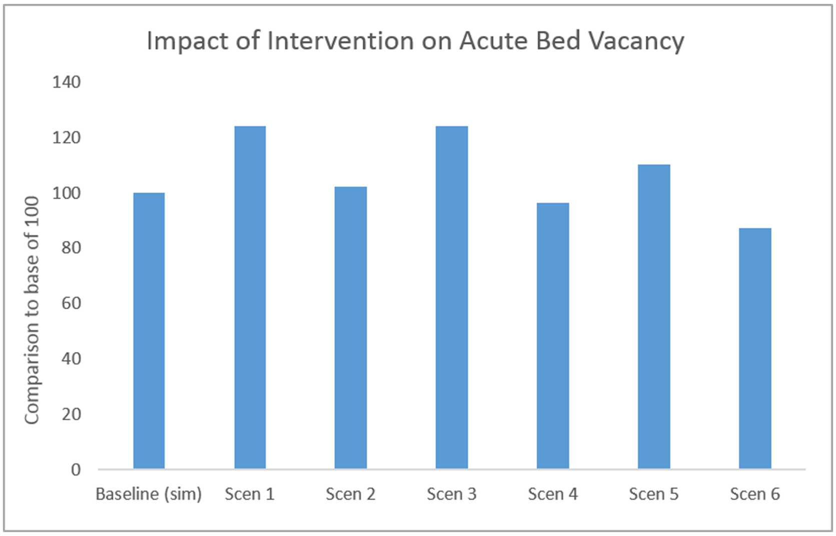


FIGURE 16 Comparison of scenarios—acute bed vacancy [Colour figure can be viewed at wileyonlinelibrary.com]

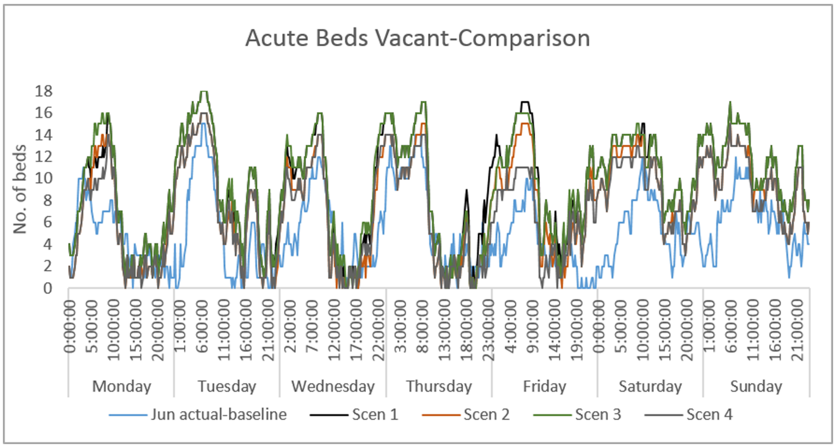


FIGURE 17 Acute bed vacancy dynamics [Colour figure can be viewed at wileyonlinelibrary.com]

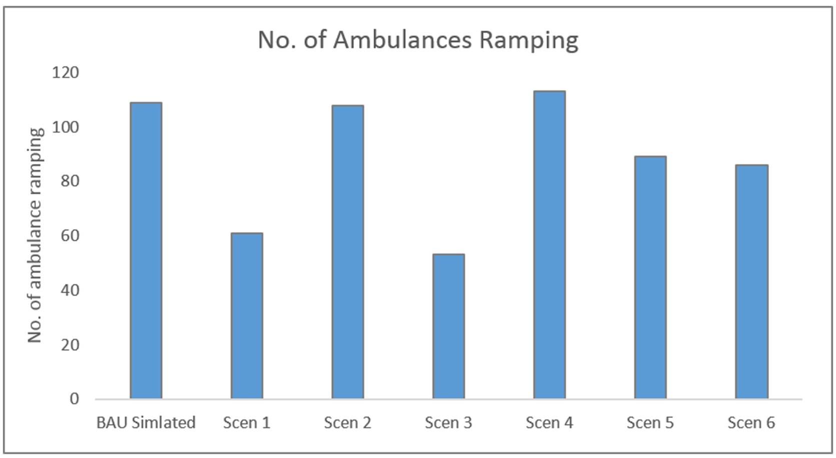
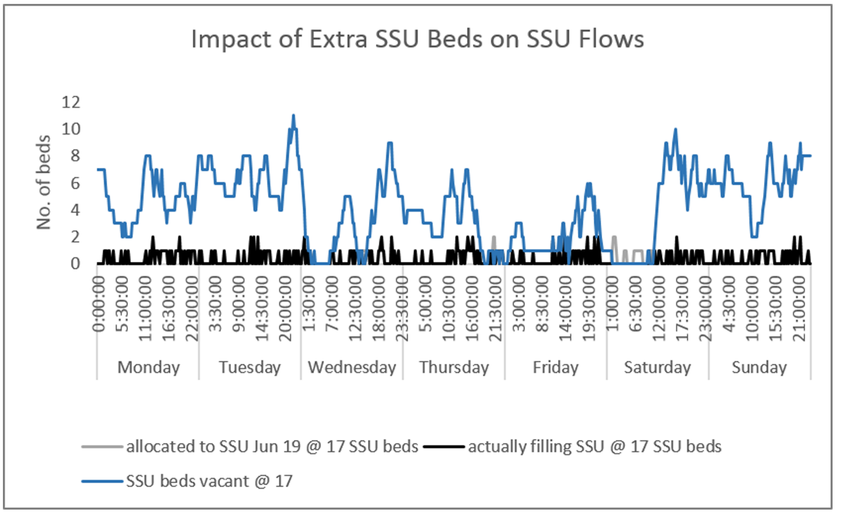


FIGURE 18 Comparison of scenarios—ambulances ramping [Colour figure can be viewed at wileyonlinelibrary.com]

Scenario 1, which adds two acute beds, appears to relieve ramping on the basis of the arrival flow experienced in this BAU week. This is not unexpected or revelatory. Flow is what matters in an ED. Adding ED acute beds will be of limited value if patients cannot be seen by the doctor, meaning no capacity to flow to testing or further doctor consultations, short-stay beds, or wards. Scenario 3 enables flow by adding additional short-stay beds and doctors to support the addition of extra acute beds. The model behaves as expected and shows improved impact, namely, lower ramping and improved residency averages (although this is not an impact factor being reported for

FIGURE 19 Short-stay unit bed dynamics [Colour figure can be viewed at wileyonlinelibrary.com]



this study). The singular addition of an extra doctor for the day shift every day except Saturday does not improve ramping and at times appears to make it worse.

Scenario 2, which adds an extra three short-stay beds without any change to other modifiable factors, on the surface appears to do little to improve ramping. This does not infer that the number of short-stay beds is not important. On deeper investigation into the flows into the short-stay beds vacant stock in the simulation, the short stay does flow more freely with extra beds but flow still blocks at certain times even with the extra short-stay beds, as indicated in Figure 19.

4 | DISCUSSION

Acute bed utilization is cyclical, and the model can reliably replicate this cyclicality across all weeks tested. Queueing will be experienced at times of peak bed use, and the model clearly shows this impact. There appears to be a predictability to the busy times in the ED when demand will exceed capacity, and the consequence of this is that patients arriving by ambulance will remain on a stretcher awaiting an acute bed (ramping). Increasing the capacity of acute beds and short-stay beds into which many acute patients flow or doctors on roster are levers with which to facilitate flow and manage waiting times but there is a trade-off. The more facilities deployed to alleviate blockage during peak periods, the more facilities being underutilized during the quiet periods. If the choice is increasing capacity by hiring more doctors or adding acute beds, the model suggests that the more effective intervention for improving timely access to emergency care as measured by improved patient flow is increasing the capacity of acute beds. Figures 16 and 17 show that greater acute bed capacity (Scenario 1) acted to alleviate pressure; however, it also adds to underutilization during the quiet times. The model shows that the addition of acute beds alone does not yield the best flow outcome nor does the sole addition of short-stay beds. ED dynamics are all about enabling flow. The addition of short-stay beds will impact flow if these beds are full when acute flow pressure exists and if the threshold number of doctors is deployed to ensure patients can clear the ED. For the BAU week, there were some periods when both acute and short-stay beds were full at the same time. The optimal outcome for improving ramping (flow) was modifying all three levers: acute beds, doctors, and short-stay beds (Figure 18). The reason is apparent. The extra acute beds open up capacity at the front end, however that capacity is enabled by the threshold number of doctors being on and having short-stay beds to flow to at the right times. The simulation model appears to enable these nuances and thresholds to be explored in detail and flow to be optimized. The short-stay bed additions may also influence the time patients spend on stretcher; however, the pilot model cannot provide this information.

The model insights affirm the importance of managing the interdependent elements in the ED if flow is to be optimized.

The model shows that under certain dynamics, the addition of an extra doctor to remove blockages can be counterintuitive. The value of that doctor is a function of the resource interdependencies at the time the extra doctor is added. According to Figure 18, an additional doctor on day shift does not measurably relieve ramping. The model also suggests that there may be thresholds on the addition of short-stay beds to improve flows. This dynamic requires closer attention in future work as it is complex, and the exit out of short stay in the pilot model currently uses a calibrated variable. It is possible that the calibrated variable could be distorting insights. A goal of future work is to break the calibrated variable down into material and information flows that explain the delayed releases. Short-stay doctors rostered on will be a major component of this.

An SD model is an aggregate model at the system level so it will not pick up nuanced patient-level dynamics. There is value in not incorporating all the detail complexity. Strategy should not respond to every operational nuance. The risk of doing so is more pronounced oscillation in resource deployment as the system overshoots and undershoots desired goals, which can be costly and frustrating. This behavioural model is accurately predicting the pattern of beds use, both the peak times and times when utilization is low, suggesting that the model can validly replicate patient flow dynamics in the ED. The value of the stocks and flows data approach is that it provides the user with a visual understanding of accumulations and the flows that a mental model cannot deliver. The actual utilization of beds is highly cyclical with pronounced peaks and troughs owing to the slower flow rates of patients between 11:00 pm and 8:00 am. In a dynamically busy ED where staff turnover is every 8 to 10 hours, it must seem to the staff that beds are always full; however, the visual of the stock suggests otherwise.

There is a calibrated delay in the model for exiting short-stay beds. This delay to exit short-stay beds varies in each of the five runs. The ED acute bed is the entry point for a patient's journey through an acute pathway. For a minimum of 50% of patients, behaviour over time data suggests that the short-stay bed is the exit point. If the simulation closely matches historical data, then it has been assumed that the flow dynamics reasonably represent reality. The delay variable represents processes in short stay that impact release such as the short-stay doctors on roster. Significantly, as an example, the recalibration for the October data set matched in patterning to the February 2017 delay but differed in amplitude of wave, which was not surprising. The higher ratio of experienced doctors combined with the slight increase in doctors rostered on post a contracted increase in ambulance arrivals would have insured protocols for departures were faster.

Those in the system at midnight complicate the model. For the week of February 2018, the model data diverge from the actual acute bed utilization data from midnight on Monday evening until lunchtime Tuesday. At this time, the short-stay beds were not blocking theflow. What happened was that the acute beds, in the early hours of Tuesday morning, were full with Monday's late acute arrivals. Abnormally, 16 acute beds were full at midnight on the fifth, which is an outcome the system-level model did not and cannot predict. Coinciding with this utilization of capacity in acute was only one or two rostered decision-making doctors (higher than resident status) being available (not factoring in call doctors) to handle the build-up in acute (or possibly contributing to it). The model does not track individual acuities or patient attributes and cannot prioritize higher acuity patients or treat some patients faster than others as would happen in emergency cases. Not being able to account for detail dynamics is one of the weaknesses of the SD approach, but it is also a strength as the forest not the trees view informs its strategic value.

Resourcing and the feedbacks between resources is a critical determinant of performance. The model currently does not differentiate between experienced doctors (consultants, senior health officers, and registrars) who can expedite patient treatments more quickly than junior doctors whom protocol requires must consult senior doctors prior to making decisions or ordering tests. Worker burnout is outside scope. Break times and time to handover as shifts change have not been explicitly modelled. The role of nurses is not explicit in the model; however, the delays specified would reflect wider resourcing and ward availability. Doctor's breaks are not considered and neither is seasonality. Some of these dynamics, although beyond the scope of this pilot model, are scoped for the next stage of this work.

5 | CONCLUSION

This study is a work in progress. The pilot SD model shows initial promise; however, it should only be regarded as having taken the first steps. This model provides a tool with which to explore trade-offs and how a variety of interventions interact to impact multiple outcomes at the same time.

Applying the SD modelling framework to the ED has put a spotlight on the interdependencies in this complex system and provided a communication tool for healthcare professionals, managers, and data analysts. The simulation model through scenario analysis appears to show which levers effectively reduce backlogs to improve access to care; however, assumptions should be continuously challenged and related system components currently treated as endogenous should be built out in stock and flow form (e.g., ambulance arrivals and ward dynamics). It is the authors' intention to progressively document this continuing application of system dynamics science to improving access to emergency care.

The behaviour over time data and model conceptualization to inform the model's architecture provided valuable insights into internal and external trends and behaviours such as consistency in patterning of arrivals, patterns in acute and FT presentations, ward transitions, and time journeys. Although valuable for model construction, regularly current data feeds to update the model parameters would be ideal in this type of application where seasonality in particular is a factor in system behaviour.

Reid et al. (2005) spoke of a partnership between data analysts, healthcare managers, and healthcare professionals capable of delivering improvements in healthcare service delivery. SD was one of the tools they proposed as having the potential to radically improve the quality and productivity of healthcare. The outputs of this study are encouraging. The pilot model insights suggest this is a tool capable of having strategic value and policy impact in an area of healthcare that is facing significant challenges and for which the problems seem intractable. It is worth further investigation.

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ORCID

Sue McAvoy https://orcid.org/0000-0001-6886-7039

REFERENCES

Calder, M., Craig, C., Culley, D., de Cani, R., Donnelly, C. A., Douglas, R., … Hargrove, C. (2018). Computational modelling for decision-making: Where, why, what, who and how. *Royal Society Open Science*, *5*(6), 1–15 172096. https://doi.org/10.1098/rsos.172096

Caro, J. J., Briggs, A. H., Siebert, U., & Kuntz, K. M. (2012). Modeling good research practices—Overview: A report of the ISPOR-SMDM modeling good research practices task force–1. *Medical Decision Making*, *32*(5), 667–677. https://doi.org/10.1177/0272989x12454577

Government, A. (2017). Emergency department care 2016-17. Retrieved from Canberra: https://www.aihw.gov.au

McAvoy, S., Staib, A., & Birch, S. (2018). Models of evaluation under ceteris imparibus. *In Press.* https://doi.org/10.1002/sres.2615Is

Messina, C. (2017). *The UN leadership framework: A catalyst for culture change at the UN.* Retrieved from

Mohiuddin, S., Busby, J., Savovic, J., Richards, A., Northstone, K., Hollingworth, W., … Vasilakis, C. (2017). Patient flow within UK emergency departments: A systematic review of the use of computer simulation modelling methods. *BMJ Open*, *7*(5), 1–14 e015007. https://doi.org/10.1136/bmjopen-2016-015007

Organisation for Economic Co-operation and Development. (2017). *System approaches to public sector challenges.* Retrieved from Paris:

Paul, S. A., Reddy, M. C., & DeFlitch, C. J. (2010). A systematic review of simulation studies investigating emergency department overcrowding. *Simulation-Transactions of the Society for Modeling and Simulation International*, *86*(8-9), 559–571. https://doi.org/10.1177/0037549710360912

Reid, P. P., Compton, W. D., Grossman, J. H., & Fanjiang, G. (2005). *Building a better delivery system: A new engineering/-health care partnership (Vol. 15).* Washington, DC: National Academies Press.

Research, A. f. H. P. a. S. (2009). *Systems thinking for health systems strengthening.* Retrieved from

Richmond, B. (1993). *Systems Thinking: Critical Thinking Skills for the 1990's and Beyond*. System Dynamics Review, *9*(2), 113–133.

Russell, L., & Dawda, P. (2013). Lessons for the Australian healthcare system from the Berwick report. *Australian Health Review*, *38*(1), 106–108. https://doi.org/10.1071/AH13185

Salmon, A., Rachuba, S., Briscoe, S., & Pitt, M. (2018). A structured literature review of simulation modelling applied to emergency departments: Current patterns and emerging trends. *Operations Research for Health Care.*, *19*, 1–13. https://doi.org/10.1016/j.orhc.2018.01.001

Staib, A., Sullivan, C., Prins, J. B., Burton-Jones, A., Fitzgerald, G., & Scott, I. (2017). Uniting emergency and inpatient clinicians across the ED–inpatient interface: The last frontier? *Emergency Medicine Australasia*, *29*(6), 740–745. https://doi.org/10.1111/1742-6723.12883

Sterman, J. D. (2000). *Business dynamics: Systems thinking and modeling for a complex world.* Boston: Irwin/McGraw-Hill.

Warren, K. (2015). *Strategy dynamics essentials*: Strategy Dynamics Limited.

Zimmerman, L. (2019). *Supporting locally calibrated modeling at scale with front-line clinical teams using a transparent data user interface.* Retrieved from USA: lindsey.zimmerman@va.gov

Zimmerman, L., Lounsbury, D., Rosen, C., Kimerling, R., Trafton, J., & Lindley, S. (2016). Participatory system dynamics modeling: Increasing stakeholder engagement and precision to improve implementation planning in systems. *Administration and Policy in Mental Health and Mental Health Services Research*, *43*(6), 834–849. https://doi.org/10.1007/s10488-016-0754-1

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