



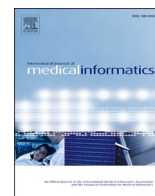
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## Resuming elective surgery after COVID-19: A simulation modelling framework for guiding the phased opening of operating rooms

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## ABSTRACT

**Objective:** To develop a 2-stage discrete events simulation (DES) based framework for the evaluation of elective surgery cancellation strategies and resumption scenarios across multiple operational outcomes.

**Materials and Methods:** Study data was derived from the data warehouse and domain knowledge on the operational process of the largest tertiary hospital in Singapore. 34,025 unique cases over 43 operating rooms (ORs) and 18 surgical disciplines performed from 1 January 2019 to 31 May 2020 were extracted for the study. A clustering approach was used in stage 1 of the modelling framework to develop the groups of surgeries that followed distinctive postponement patterns. These clusters were then used as inputs for stage 2 where the DES model was used to evaluate alternative phased resumption strategies considering the outcomes of OR utilization, waiting times to surgeries and the time to clear the backlogs.

**Results:** The tool enabled us to understand the elective postponement patterns during the COVID-19 partial lockdown period, and evaluate the best phased resumption strategy. Differences in the performance measures were evaluated based on 95% confidence intervals. The results indicate that two of the gradual phased resumption strategies provided lower peak OR and bed utilizations but required a longer time to return to BAU levels. Minimum peak bed demands could also be reduced by approximately 14 beds daily with the gradual resumption strategy, whilst the maximum peak bed demands by approximately 8.2 beds. Peak OR utilization could be reduced to 92% for gradual resumption as compared to a minimum peak of 94.2% with the full resumption strategy.

**Conclusions:** The 2-stage modelling framework coupled with a user-friendly visualization interface were key enablers for understanding the elective surgery postponement patterns during a partial lockdown phase. The DES model enabled the identification and evaluation of optimal phased resumption policies across multiple important operational outcome measures.

**Lay abstract:** During the height of the COVID-19 pandemic, most healthcare systems suspended their non-urgent elective surgery services. This strategy was undertaken as a means to expand surge capacity, through the preservation of structural resources (such as operating theaters, ICU beds, and ventilators), consumables (such as

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personal protective equipment and medications), and critical healthcare manpower. As a result, some patients had less-essential surgeries postponed due to the pandemic. As the first wave of the pandemic waned, there was an urgent need to quickly develop optimal strategies for the resumption of these surgeries. We developed a 2-stage discrete events simulation (DES) framework based on 34,025 unique cases over 43 operating rooms (ORs) and 18 surgical disciplines performed from 1 January 2019 to 31 May 2020 captured in the Singapore General Hospital (SGH) enterprise data warehouse. The outcomes evaluated were OR utilization, waiting times to surgeries and time to clear the backlogs. A user-friendly visualization interface was developed to enable decision makers to determine the most promising surgery resumption strategy across these outcomes. Hospitals globally can make use of the modelling framework to adapt to their own surgical systems to evaluate strategies for postponement and resumption of elective surgeries.

## 1. Background and significance

During the height of the COVID-19 pandemic, most healthcare systems suspended their non-urgent elective surgery services. This strategy was undertaken as a means to expand surge capacity, through the preservation of structural resources (such as operating theaters, ICU beds, and ventilators), consumable resources (such as personal protective equipment (PPE) and medications), and manpower. Non-urgent elective procedures may also unnecessarily contribute to increased risk of spreading the coronavirus within facilities. As a result, some patients had their needed, but less-essential surgeries postponed [1]. While short-term postponement of these elective surgeries may be tolerable, there is potential to result in worse outcomes for patients if their surgeries are delayed for a prolonged duration. As the first wave of the pandemic waned, there was an urgent demand to resume these postponed surgeries whilst managing the peacetime workloads in an optimal manner.

Professional bodies and societies around the world have weighed in this issue by releasing guidelines and principles for the safe resumption of elective surgical services [2–5]. Most notably, the American College of Surgeons, American Society of Anesthesiologists, Association of Peri-Operative Registered Nurses, and American Hospital Association have jointly issued a suggested roadmap that delineates four main categories of issues that should be addressed in such planning [5]. A phased reopening of the operating rooms (OR) has been recommended as one of the key strategies for safe resumption which transcends all of these four categories. A phased reopening strategy, however, is not a straightforward approach. The rate of increase in reopening OR slots needs to be balanced against multiple competing aims. For example, the number and surgical case-mix that is allowed to be booked needs to be matched with the availability of general and intensive care beds (with adequate resources and staffing), assessment of clinical acuity, load of backlogged cases and optimal utilization of OR slots. Furthermore, the strategy must be flexible and agile enough in case of sudden re-resurgence of COVID-19 in the community.

In view of these complex requirements, there is a need for data-driven tools and simulation models to guide policymakers and hospital administrators on the best OR reopening strategies. There is currently a paucity of published literature on candidate models that could be used for this purpose. In this paper, we aim to describe the development of one such modelling framework that addresses the following:

- (1) How long will it take to clear the backlog given ongoing surgical demands?
- (2) What are the best strategies to bring back postponed surgeries in order to achieve the business-as-usual scenario before COVID-19 in the most cost-effective and efficient means possible?
- (3) How can we clear the backlog in a clinically responsible way without having overly extended wait times for surgical patients?
- (4) How can we ensure that the resumption process will not result in high levels of utilization for surgical staff?
- (5) How can we deal with potentially unexpected scenarios resulting from future surge in COVID-19 cases during the resumption period?

The original process for deciding on resumption strategies relied largely on the use of Microsoft Excel by planning teams. We developed a 2-stage modelling framework based on K-means clustering [6] and discrete events simulation (DES) deployed in Python programming language [7] in order to deal with large amounts of data with highly volatile scenarios in a sustainable system. The DES model can interface with new data and consider alternative elective surgery management strategies as the pandemic evolves with resurgent waves of infections. Updated models can be easily derived without having to deal with bulky spreadsheets that have to be manipulated in an ad-hoc manner. A user-friendly visualization interface was also developed to support managers and administrators.

This study was exempted from Centralized Institutional Review Board (CIRB) review of the Singapore Health Services (opinion date 26 May 2020, number 2020/2470) as it was considered a service improvement project using routinely collected anonymous data.

## 2. Data and methods

Singapore is a city-state in Southeast Asia with 5.7 million people and a diverse ethnic composition. The study hospital (SH) is Singapore General Hospital (SGH) which is the largest comprehensive public hospital in Singapore. SGH comprises of more than 30 clinical disciplines and approximately 1,700 inpatient beds. The hospital saw more than 25,000 surgeries and had 18 ICU beds in 2019. The number of ICU beds can be surged up to 40 beds and subsequently up to 200 beds (in phases) during a pandemic. The surgical services comprise of 43 ORs, where the planned response included essential drugs rationing (e.g. propofol, fentanyl and muscle relaxants), conversion of ORs into ICU facilities, and the re-designation of medical as well as nursing manpower for taking care of COVID patients. The detailed response plan has been described in a previous publication [8].

We performed a retrospective, single-center study to develop data-driven simulation models to guide policymakers and hospital administrators on the best OR resumption strategies. Data for this study was derived from the SH's Electronic Medical Record (EMR) based on Sunrise Clinical Manager (Allscripts, Illinois, USA) which is integrated with data from multiple other healthcare transactional systems (including administrative and ancillary systems) and stored in an enterprise data warehouse, the electronic Health Intelligence System (eHINTS) [9]. Anonymized data from the Perioperative Registry of the SH was used. Data included patient demographics, surgical listing details, operating room utilization details, and hospital admission history for all elective and emergency surgeries done at the SH's Main Operating Theatre (MOT) and the Ambulatory Surgical Centre (ASC) from January 2019 to May 2020.

Non-essential elective surgeries were systematically reduced from 7th February 2020 in response to an increasing number of COVID-19 cases in Singapore. Further reduction in the elective surgical listing was mandated from 7th April 2020 in response to a nationwide partial lockdown (known as "Circuit Breaker" measures) instituted by Singapore [10]. Resumption of surgeries was assumed to start after the end of the lockdown period. The modelling framework thus consisted of two stages. Stage 1 evaluated the surgery reduction patterns during the

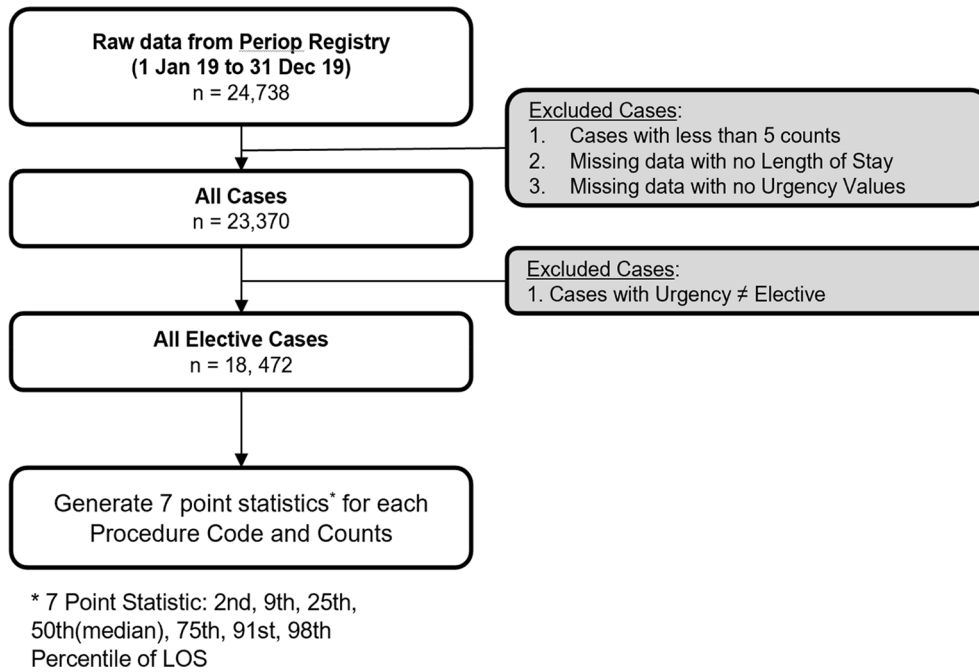


Fig. 1. Data cleaning process for the unsupervised cluster analysis.

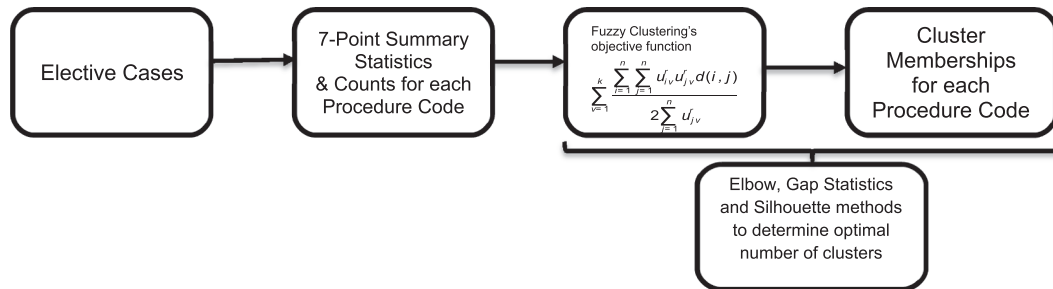


Fig. 2. Flowchart for the fuzzy clustering algorithm.

partial lockdown period, whilst Stage 2 considered the reduction patterns in Stage 1 as inputs in the DES model for evaluation of alternative resumption strategies. The surgery reduction patterns will be derived from unsupervised cluster analysis and the clusters will be used in Stage 2 for the evaluation of alternative resumption strategies. The primary outcomes evaluated by the framework were (1) bed demands for surgical patients; (2) OT slots utilization; (3) waiting time to surgery, and (4) time to clearance of backlogs.

• Stage 1: Evaluating the Surgery Reduction Patterns

To assess the impact on overall surgical load due to the postponement of cases, retrospective data from 34,025 unique cases over 43 operating rooms (ORs) (including ASCs, MOTs, specialized urology suites and others), all surgeries from 18 surgical disciplines performed in the SH from 1 January 2019 to 31 May 2020 were extracted from the EMR for the study. Since the main objective of this simulation model was to evaluate the reduction and subsequent resumption of elective surgeries, non-elective surgeries and surgeries with rare (<5 counts) procedure codes were removed. Differences in caseloads between January 2019 to May 2019 and January 2020 to May 2020 were used to obtain the estimated reduction in caseloads. To obtain a representative sample of surgical cases over a yearly period, 24,738 unique cases performed from 1 January 2019 to 31 December 2019 from this dataset was used to perform K-means clustering to identify cluster of surgical procedures.

Cases with no length of stay or urgency status values were also excluded from the analysis. Finally, 18,472 elective cases were used in the clustering analysis (see Fig. 1).

Clustering of procedure codes based on the Ministry of Health's Table of Surgical Procedures [11] was done to derive the surgery reduction patterns across all procedures. A data driven approach was found to be more suitable for the characterisation of reduction rates compared to the use of predefined criteria which assumed only certain procedure types were postponed based on literature evidence [1,12]. The clusters derived from the analysis were identified based on length-of-stay(LOS) statistics and volume of surgeries.

The cluster labels of surgical procedures captured in the EMR were derived from the fuzzy K-means clustering algorithm [7] and the distributions of these postponed procedures were used to simulate elective reduction patterns. 18,472 elective cases were first grouped according to the procedure code that was associated with the elective case. 7-point statistics for each surgical procedure code were generated using the LOS (in days) associated with each case. The 2nd, 9th, 25th, 50th (median), 75th, 91st, 98th Percentile and total count (n) were used to identify the clusters. The elbow method, gap statistics and silhouette methods were used to determine the optimal number of clusters to be used in the analysis. Procedure codes were labelled with the cluster labels identified through this analysis and can be used prospectively for new cases with such procedure codes. The steps for the fuzzy clustering analysis is shown in Fig. 2. A descriptive analysis was performed to

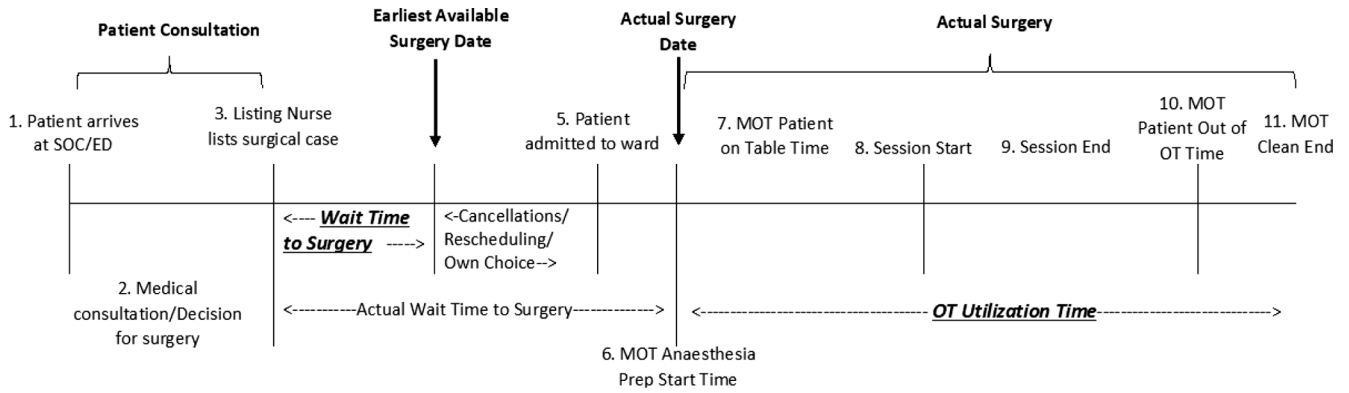


Fig. 3. Timeline of events for the surgical scheduling process.

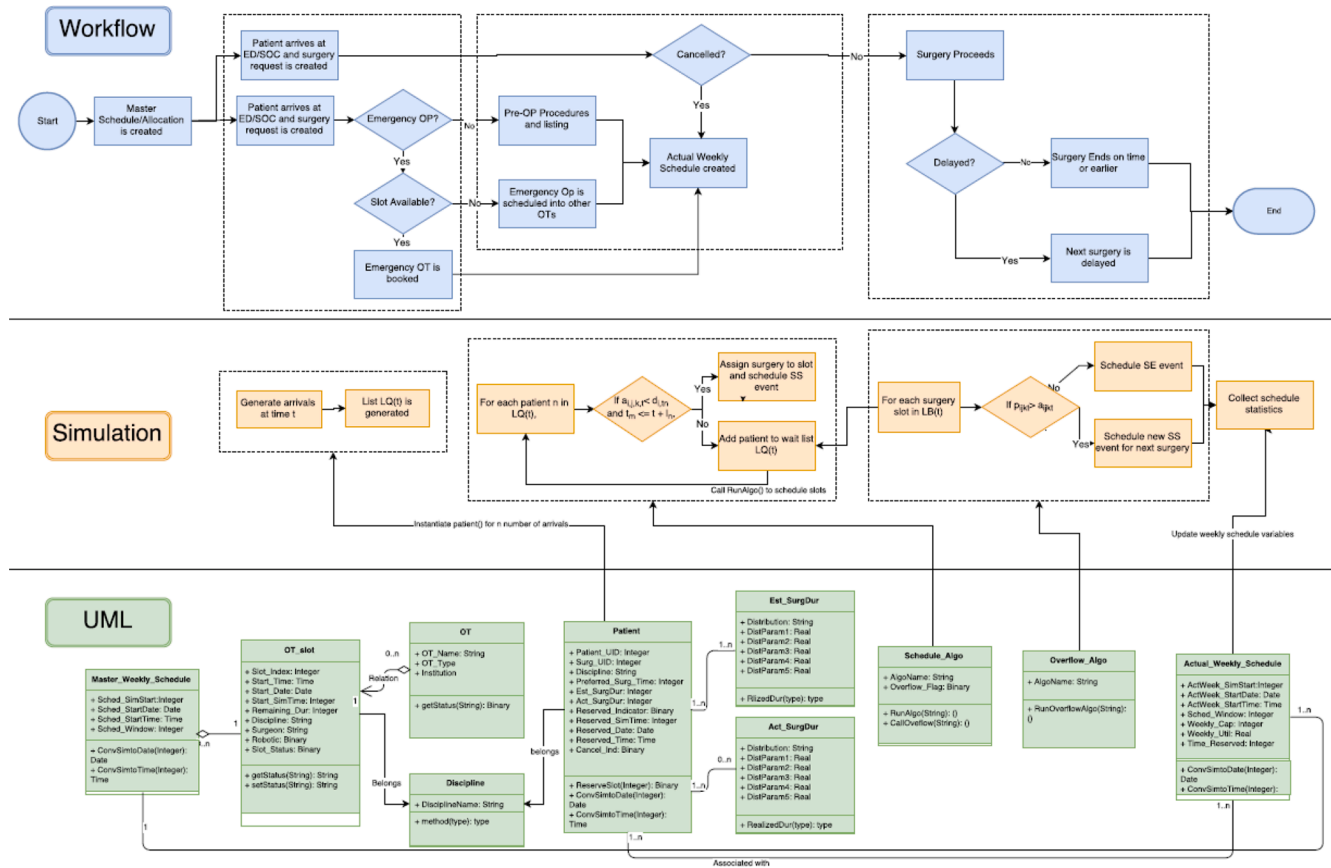


Fig. 4. UML diagram depicting inter-twined relationships and information flows across various stakeholders and subsystems.

validate the clusters with inputs from OR clinicians and OR management executives.

- Stage 2: DES model for the Evaluation of Resumption Strategies

### 2.1. DES model

To assess the impact of various resumption strategies, a DES model that was developed earlier for OR listing processes [13] was updated to describe the processes during the study period. The DES model was deployed using Python 3.6 [8]. Pandas [14] and Numpy [15] packages were used to implement distributional parameters in the model. 23 elective ORs for 18 surgical disciplines and 2 emergency ORs from our

institution were included in the simulation model. The model captured the detailed processes from the point of the first listing until after the patient exits the hospital, capturing both OR and inpatient bed management processes. The process understanding developed through in-depth interviews with nurses, surgeons, anesthesiologists, and scheduling staff were incorporated to develop the operational constraints of the simulation model. The OR allocation schedules from 2019, empirical distributions for the arrival rates of patients, duration of each surgical procedure and in-hospital length of stay and the distribution of cancelled surgeries derived from Stage 1 were fed as inputs into the simulation model. We assumed that the MOTs are operational for five days per week with 525 min of available surgery time per working day for each OT (capacity). The operating policies incorporated into the model are described as follows (see Fig. 2 for the flow of events and definition of

**Table 1**  
Monthly Surgery Loads across OR locations from 1 Jan 2019/2020 to 31 May 2019/2020.

Location	2019					2020				
	Jan	Feb	Mar	Apr	May	Jan	Feb	Mar	Apr	May
ASC	433	348	499	455	440	329	0	265	183	85
MOT	1404	1222	1515	1541	1544	1326	1111	1179	1104	906
URO	220	151	198	226	243	199	56	1	5	6
Others	92	74	92	92	88	147	145	174	151	94

the performance indicators):

- (1) Patients arrive at the Emergency Department (ED) or the hospital's Specialist Outpatient Clinics (SOCs). If they require surgical treatment, a surgery request is made to the listing nurses in the appropriate operating theatres.
- (2) The listing nurse search for an available OT slot to list the surgery case.
- (3) The available slots are allocated to scheduled surgeries during the listing process.
- (4) Emergency surgical cases are first listed into the 2 dedicated Emergency ORs. However, if these ORs are being utilized and are unavailable, emergency cases may be listed in one of the available elective OR.
- (5) After the surgical case has been listed or scheduled into a particular OR slot, it can be cancelled or rescheduled to another date.
- (6) Surgeries that extend beyond the OR daily operating duration will be attributed to OR overtimes

OR slots have been assigned to surgical disciplines through the master surgical schedules prior to the listing process. Surgeons are only able to list their cases into slots allocated according to the master surgical schedule. An exception to this scheduling policy is made if they have mutual arrangements with other surgeons and departments or if the slot has been made available for open booking during the open access period. OR utilization time is defined as the time taken from when the anesthetist begins to prepare the patient for surgery, up to the point when the OR is cleaned and ready for use for the next surgery case (see Fig. 3). OR utilization is defined as the OR utilization time over total available OR time. Wait times to surgery (WTS) is defined as the date when the surgery is listed till the date of the actualized surgery, which includes the delays resulting from any cancellations and rescheduling during that period (see Fig. 3).

Patient arrivals were assumed to follow independent Poisson processes for each OR discipline, with mean inter-arrival rates estimated from the dataset. Surgical case from each discipline was generated using empirical probability distributions derived from the data. Surgical durations were modelled using discretized empirical distributions. Surgical cases are assigned to OR slots using a first-fit algorithm [26] over the possible choices of OR slots. Constraints on the allocation of OR slots to surgeons and departments were derived from master surgical schedule. Hospitalization could occur a day before or on the day of surgery. If the patient requires admission to one of the intensive care (ICU) or high dependency (HD) units, a bed in the ICU or HD will be secured prior to the operation. As this is meant to be a continuous flow process with high variability, there is a need to establish dynamic objects which are robust and flexible enough to incorporate the stochastic and uncertain events across the entire flow. The class diagram which captures the flow of information across various stakeholders and scheduling subsystems in Unified Modeling Language (UML) [27] is shown in Fig. 4.

Input statistics related to average surgical durations and caseloads, as well as outcome measures related to the ORU and WTS performance across the ORs and surgical disciplines were validated against the historical data in the baseline scenario. Apart from the ORU and WTS, other secondary indicators related to the average number of patients waiting

for surgeries, overtimes and cases listed were also compared with the historical data. Non-parametric bootstrap confidence intervals (95%) for the simulated results were developed and compared against the actual statistics derived from the historical data across all the OTs. The Kolmogorov-Smirnov non-parametric test was used to compare the difference in the actual and simulated empirical distributions of the outcome measures. A simulation warm-up period of 3 months was assumed, and identical random seeds were used in the simulation model for these validation studies.

*Evaluation of Resumption Strategies* Different resumption scenarios were evaluated against the predicted outcome measures to develop the optimal resumption strategies. The DES model was run across three distinct phases:

- (1) Phase 1: Refers to the business-as-usual (BAU) or "peacetime" period, prior to 7th February 2020
- (2) Phase 2: Reduction of surgical procedures over the period of 4 months from 7th February 2020 to the end of the nation-wide partial lockdown period on 1st June 2020
- (3) Phase 3: Resumption of surgical services belonging to Cluster 1 (the cluster with most case COVID-19 related elective postponement)

The DES model can be used to evaluate various potential resumption strategies in terms of the volume of resumption across the postponed elective procedures. Amongst the various strategies evaluated with the DES model, we describe the following more significant configurations of resumption strategies in phase 3 for this study:

- Strategy 0: Full resumption from Month 1
- Strategy 1: 25% resumption incrementally from Month 1 to Month 4
- Strategy 2: 50% resumption incrementally in Month 1 and Month 2
- Strategy 3: 50% resumption incrementally in Month 1 and Month 3
- Strategy 4: 50% in Month 1, followed by an additional 25% in Month 2 and 3

The simulation was run for a period of 36 months, with a warm-up period of 5 months from the start of the simulation, and a cool-down period of 4 months from the end of the simulation run. The stable regime from Month 5 to Month 20 corresponded to the period from 31 Dec 2019 till 31 Jan 2022. The postponement of surgical cases was implemented from the start of Month 9 to the end of Month 11, corresponding to the April - Jun 2020 period. The partial resumption of the cases started from Month 12 onwards to Month 17, corresponding to the July - Dec 2020 period and full resumption of cases after this period. This timeline mirrors the historical sequence of interventions in 2020.

The simulation results were used in evaluating outcomes from the various strategies. Statistics from the outcomes were derived from 10 replications of the simulation runs for each scenario. Each replication of the simulation for each strategy was run with a different random seed for the random variables used in the simulation model. The peak/average values and time of resuming back to BAU (since the BAU scenario was our baseline) for the outcome measures (bed demands for surgical patients, OR utilization and waiting time to surgery) were evaluated and compared for each resumption strategy.

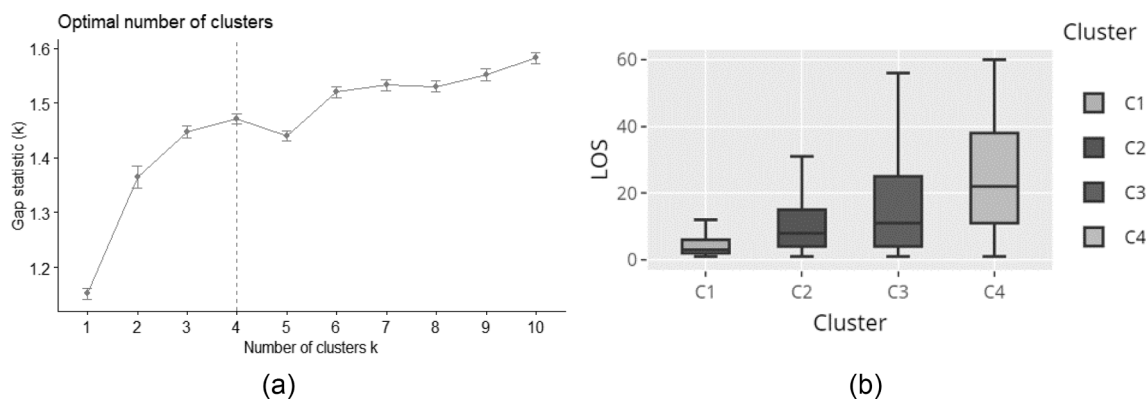


Fig. 5. (a) Cluster identification using the Gap Statistics; (b) Descriptive statistics of 4 clusters.

**Table 2**  
Summary Statistics for the Cluster Analysis based on the LOS statistics.

Statistic		Cluster 1	Cluster 2	Cluster 3	Cluster 4
Length of Stay Statistics	Minimum	1	1	1	1
	1st Quartile	2	4	5	14
	Median	3	8	13	35
	Mean	5.02	13.65	25.87	46.72
	Standard Dev	5.79	18.00	33.1	45.6
	3rd Quartile	6	16	35	62
	Maximum	132	257	261	301
No of Surgeries*		12,020	3,915	1,378	959
% of Surgeries*		65.78%	21.43%	7.54%	5.25%
No of Bed days*		60,355	53,431	44,800	35,642
% Bed days*		31.07%	27.51%	18.35%	23.07%

**Table 3**  
Year-on-Year (YOY) Comparison of Surgery Loads.

Cluster	Year	Jan	Feb	Mar	Apr	May
C1	2019	1252	1173	1556	1586	1538
	2020	1244	696	911	669	477
	Percent change	-1%	-41%	-41%	-58%	-69%
C2	2019	261	282	335	337	335
	2020	317	283	290	299	285
	Percent change	21%	0%	-13%	-11%	-15%
C3	2019	94	101	112	120	131
	2020	123	117	165	177	127
	Percent change	31%	16%	47%	48%	-3%
C4	2019	84	115	129	105	117
	2020	152	126	128	177	118
	Percent change	81%	10%	-1%	69%	1%

### 3. Results

**Stage 1:** A year-on-year comparison of the surgical load was made for 5 months from 1 Jan till 31 May across years 2019 and 2020. The results are shown below for ASCs, MOTs, specialized Urology ORs (URO) and other ORs in Table 1. The K-means cluster analysis revealed discernible patterns of hospital bed-days demand across the 1,304 different surgical codes in the system. A value of  $k = 4$  was selected as the optimal number of clusters to be used in the analysis based on results of the elbow method, gap statistics and silhouette methods [7]. Fig. 5(a) shows the cluster identification result using the gap statistics and Fig. 5(b) shows the distribution of the 4 clusters. The following clusters were derived from the dataset (Fig. 4):

- (1) Cluster 1 consists of 65.78% of surgeries with short LOS (2–6 days) and accounted for 31.07% of bed days

- (2) Cluster 2 consists of 21% of surgeries with moderate LOS (4–16 days) and accounted for 27.51% of bed days
- (3) Cluster 3 consists of 7.5% of surgeries with long LOS (5–35 days) and accounted for 18.35% of bed days
- (4) Cluster 4 includes 5.25% of surgeries with significantly longer LOS (14–62 days) and accounted for 23.07% of bed days

The summary statistics for the LOS of the clusters are presented in Table 2. From the descriptive analysis, a 31.4% reduction was observed in the number of surgeries performed during the COVID-19 restrictions period compared to the same period in the preceding year. When analyzed by cluster, most of the reduced surgery listings came from cases within cluster 1 (see Table 3 and Fig. 6). Cluster 1 accounted for 41 to 69% reduction of surgeries from February to May in 2020. Surgeries in Cluster 1 accounted for 66% of all surgeries performed with a median post-operative LOS of 3 (IQR:4) days. Cluster 2 experienced a less significant reduction year-on-year. Approximately 76.3% of orthopedic, 86.7% of urology and 50% of general surgeries were labelled as belonging to cluster 1. The top 10 number of surgeries in cluster 1 were surgeries related to total knee replacement, hernia, gallbladder, breast cancer, urethra cytoscopy, colon and spine. The top 10 number of surgeries in cluster 2 were related to surgeries on bile duct, coronary disease, bladder cystoscopy, vascular, colon and laparotomies (see Annex, Table A1).

**Stage 2:** The DES simulation model focused on the phased reopening strategies of ORs for procedures in cluster 1. The impact of full reopening and phased reopening with strategies 1–4 on the peak hospital bed demands, waiting time to surgery for backlogged cases and OR utilization was compared using the simulation model. The trajectories for the recovery of bed demand to business-as-usual (BAU) (or backlog clearance time) are shown in Fig. 7(a). It can be observed that Strategy 2 recovers to an acceptable threshold of deviation from the BAU levels at a much faster rate. However, the peak bed demand in strategy 2 is higher than Strategy 1 or 4. Fig. 7(b) shows the trajectories of OR utilization from Jan 2020 which captured the period prior to surgery reduction, during the reduction period and during the resumption period for the full resumption and 2 sequential resumption strategies. It can be observed from Fig. 7(b) that the variability in OR Utilization for Strategy 1 was more pronounced, due to the resumption of surgeries being spread out across various time points.

For the SH, we found strategies 1 and 2 were the most promising across the outcome measures. Strategy 1 showed lower peaks for bed demand (Fig. 8(a)), lower peak OR utilization rates (see Fig. 8(b)) but it took a longer time to achieve BAU levels for OR utilization (see Fig. 8(d)). However, Strategy 1 may result in more fluctuations in the OR utilization (see Fig. 7(b)). Strategy 2 resulted no significant changes in peak bed demand and OR utilization (Fig. 8(a) and (b)) and may require a longer time to return to BAU levels for OR utilization (Fig. 8(d)). However, Strategy 2 may be preferred if the clearance times across the

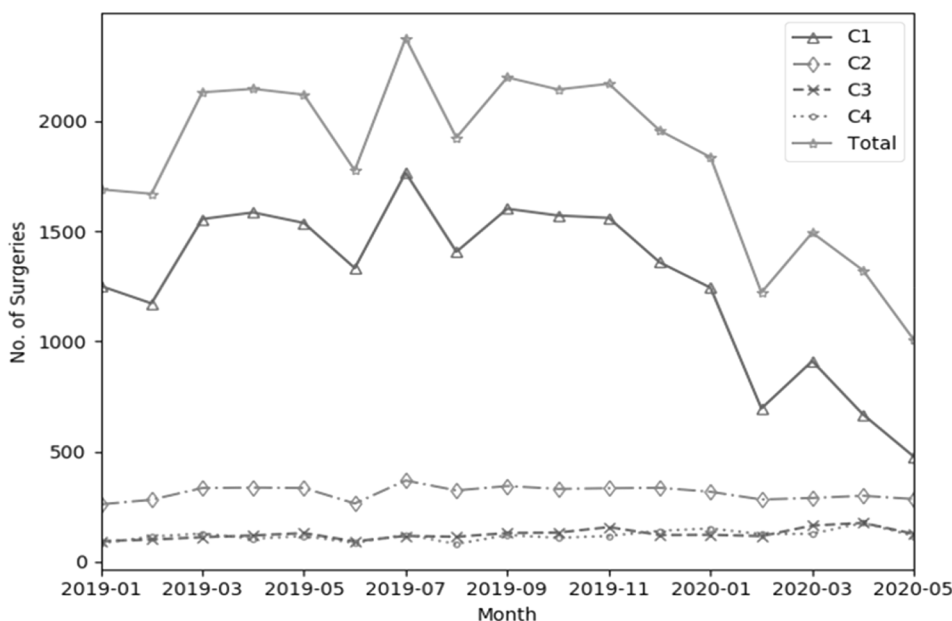
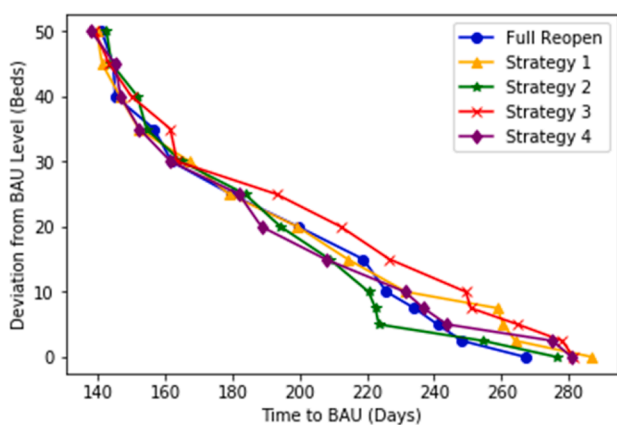
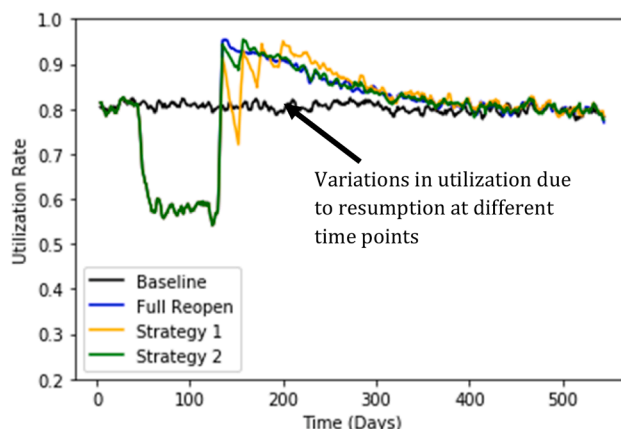


Fig. 6. Breakdown of the reduction of surgical loads across the 4 clusters.



(a)



(b)

Fig. 7. Comparison of Bed Demands and OR Utilization across 4 strategies and full resumption for: (a) Recovery of Bed Demands to BAU; (b) OR Utilization before surgery, during reduction and during resumption.

bed outcomes within a specific acceptable threshold from the BAU level (e.g., 5–10 days as shown in Fig. 7(a)). Based on the simulation runs, there is no significant impact on the peak bed demand and the time to converge to BAU levels for bed demands between Strategy 2 and full resumption (Fig. 8(a) and (c)) (see Table 4).

#### 4. Discussion

The decision to lift restrictions placed during the COVID-19 pandemic were not taken lightly. This study demonstrates how data from previous years and during the pandemic could be utilized to guide the decision for phased resumption of surgical services. In this study, data from one year pre-COVID was used to guide the analysis to demonstrate the effectiveness of such an approach. Data from multiple years prior to when COVID-19 appeared can be incorporated easily into the proposed 2-stage modelling approach. The proposed 2-stage approach made use of unsupervised learning methods to identify targeted groups of surgical procedures and a DES model to evaluate suitable resumption strategies for these groups. These findings provided

insight and guidance to postponement and resumption strategies in various stages of the pandemic as well as advance planning for future pandemic scenarios.

A number of research have discussed the issue of optimal resumption of surgical services post COVID-19 using qualitative analysis and proposed guidelines across various surgical disciplines [16–18]. A few reported studies attempted to use time series and queueing methodologies [19], mathematical modelling [20] and retrospective cohort analysis [21] to glean insights on the impact of surgical disruption and to support decisions on surgical resumption. Mathematical models have been proposed by Joshi et al. [20] with the objective of determining the optimal combination of rooms and surgical hours to minimize staff overtime during the resumption of surgical workloads. Till date, there has not been research that directly models the impact of surgical workloads and postponements jointly, based on a DES model that accounts for OR workloads, OR utilization, waiting times to surgery and backlog clearance times. Our modelling framework accounts for the tradeoffs between over-utilization (that can lead to significant over-times) and extended patient wait times. Clearance times have been



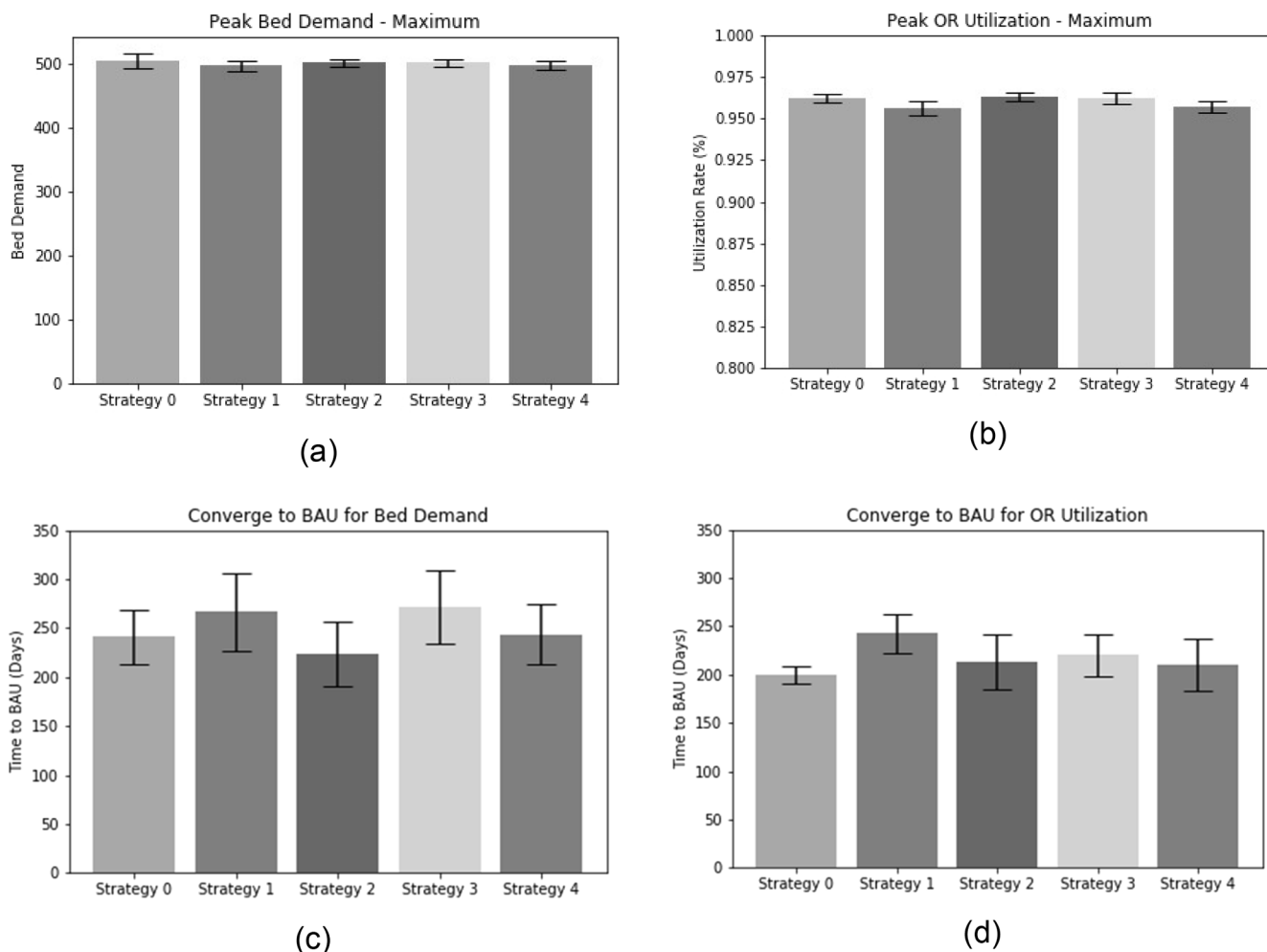


Fig. 8. Comparison of Time to Event measures across 4 strategies and full resumption with 95% confidence intervals for: (a) Peak Bed During Resumption (b) Peak OR Utilization (c) Convergence Time to BAU for Bed Demands (d) Convergence Time to BAU for OR Utilization.

Table 4  
Results from the simulation model across the various outcome measures.

Policy	Resumption Strategy	Range of Bed Demands During Resumption	Range of OR Utilization During Resumption	Range of Peak Wait Times to Surgery During Resumption	Time to Event Mean (SD)		
					Time to Peak Bed During Resumption	Converge to BAU for Bed Demands	Converge to BAU for OR Utilization
Full Resumption	Strategy 0	485.0–504.3	94.2%–96.2%	74.3–108.2	154.9 (77.5)	241.0 (45.7)	199.7 (13.6)
Sequential Resumption	Strategy 1	470.9–496.1	92.1%–95.6%	41.8–145.5	152.4 (94.5)	266.6 (64.6)	242.5 (33.7)
	Strategy 2	482.7–500.6	92.0%–96.3%	56.1–119.9	149.8 (66.1)	223.5 (53.3)	213.7 (45.6)
	Strategy 3	472.9–501.4	91.3%–96.2%	75.2–145.7	138.6 (67.2)	271.0 (60.5)	220.1 (35.8)
	Strategy 4	477.5–497.3	91.4%–95.7%	36.8–116.4	180.8 (80.3)	243.8 (49.7)	210.1 (42.9)

^ Lower bound is based on conservative estimate across 2 weeks before and after peak demands. Upper bound is the absolute maximum bed demand/OR Utilization.

estimated using queuing models before [19]. Similar to clearance times, our model estimated the time required to reach the BAU workload. In our case however, the DES model allows for estimation of the entire distribution of clearance times based on actual data across all surgical groups whereas the queuing models based on Little’s Law primarily estimates mean clearance times [19,22].

A multidisciplinary approach that considers organizational, surgical and patient factors has been advocated to triage cases [12]. Case by case assessment in the triaging process is important and should consider individual patient factors (e.g., age, comorbidities, disease severity), the surgical procedure, projected inpatient LOS and the eventual load of

backlogged cases amongst others [12]. Similar multi-factorial considerations have been observed in the SH. The types of surgeries that were reduced thus had to be characterised from a data-centric approach instead of having predefined criteria to group the surgery types that were reduced. An unsupervised learning approach does not require any prior assumption in the definition of the clusters. The clustering results provided important inputs for the downstream DES model and helped to guide decisions on the appropriate case-mix that could be listed in each phase of the resumption strategy. The postoperative LOS and volume of surgeries were deemed sufficient to derive insights and inputs to the DES model. Nonetheless, more detailed clustering can be performed using

### Surgery Scheduling Monitoring Dashboard (Division Level)

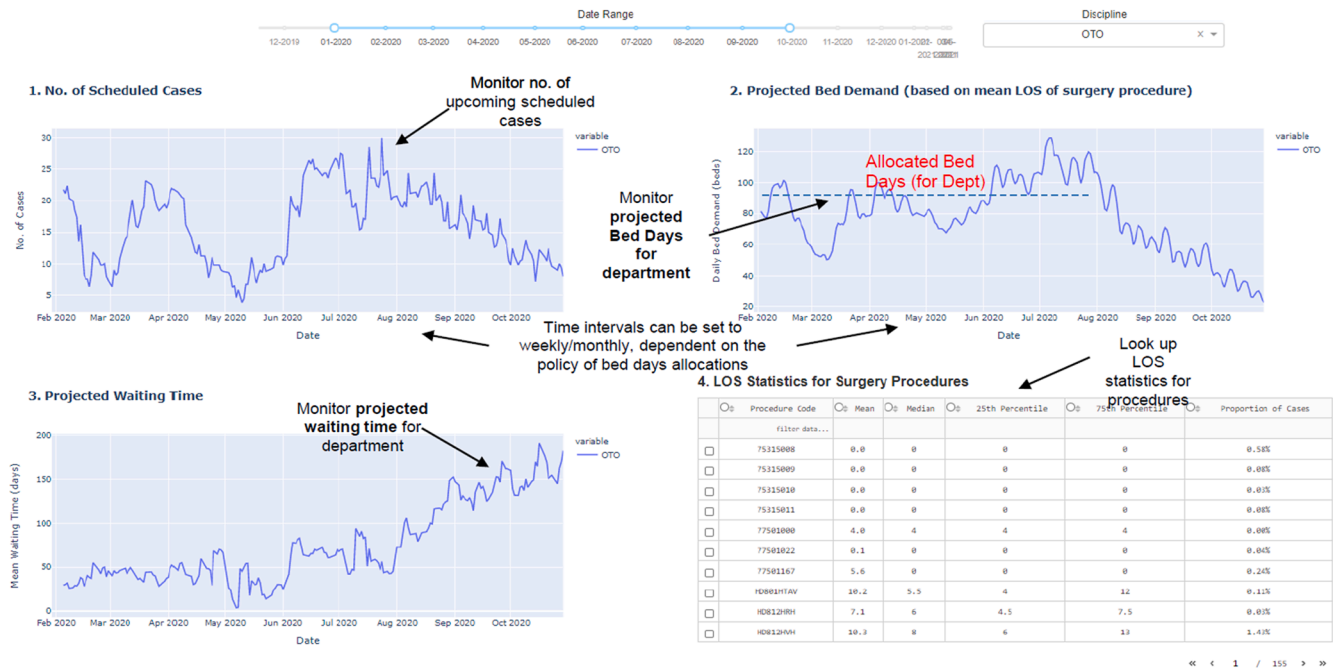


Fig. 9. Decision support dashboard for monitoring the resumption of surgical services during COVID-19.

this two-stage framework. The clustering analysis can consider additional factor such as indication and urgency, expected requirement for prolonged ventilation and the need for postoperative ICU.

To ensure that the model output was relevant not just for policy-makers but similarly for ground managers, we developed a live dashboard to monitor the historical and projected available bed days and waiting time to surgery for each surgeon and surgical discipline. This dashboard provided visibility across these measures for the weeks ahead and acted as a decision support tool on allowing the listing of elective surgical cases (See Fig. 9). As the pandemic continues to evolve with new variants and resurgence in various countries, the dashboard provides a ready means to make evidence-based OR management decisions in an agile and sustainable manner. A similar dashboard was also described in Joshi et al. [20] which included information on personal protective equipment (PPE) usage but excluded projections of bed demands. The inclusion of bed demands is critical from our hospital management perspective as trade-offs in terms of the bed demands have to be considered for non-surgical disciplines (e.g., infectious disease beds). Furthermore, stringent policies to mitigate hospital acquired infections during COVID-19 may require reduction of the number of beds in shared rooms (eg eight bedder wards) by as much as 50%. The implications of these bed reduction strategies should be also accounted for in evaluation of strategies for reduction and resumption of surgeries. PPE, ventilators and drugs were assumed to be sufficient similar to Wang et al. [19] as Singapore did not face a shortage of these essential items during the entire COVID-19 period. The postponement of such surgeries may also lead to unintended negative effects, such as disease progression due to delayed surgeries which may lead to more invasive or additional surgeries. While this is a widely recognized conundrum [1,5], our current model was not able to account for such individual-level permutations. Regardless, together with healthcare manpower, these remain important issues that a further extension of the model can account for [5].

A number of papers have recommended tiered surgery postponement strategies during the pandemic [1,23] and a phased resumption of surgeries thereafter [21,24,25]. Planning for phased resumption has to consider awareness of the pandemic situation, preparedness level of the hospital and ensure the continued delivery of safe, high quality and

high-value care for surgical patients [26,27]. The roadmap for resuming elective surgery after the COVID-19 pandemic advocated an appropriate strategy for phased re-opening of operating rooms [5]. To our knowledge, the quantitative evaluation of phased resumption strategies have not been reported in the literature, although mathematical models for the evaluation of backlog clearance and the financial impact of surgical postponements have been reported previously [19,20,21]. The results from our simulation model demonstrated that phased resumption of services will improve performance across some of the outcome measures without significant impact on other measures. Dependent on the performance measure of interest to the healthcare system, the model allows the trade-offs of various resumption strategies to be quantified and an optimal strategy to be derived. Our modelling approach allowed us to calibrate the resumption strategies and resumption targets (e.g., 25% vs. 50%), revealing the trade-offs in the resumption strategies. With a phased resumption strategy, lower peak bed demands and faster recovery to normal levels can be achieved without compromising other measures. All these insights enable the SH to identify an optimal strategy for phased opening of ORs.

The model has yet to consider the financial impact of surgical reduction and resumption strategies. A retrospective cohort analysis based on insurance claims data has been reported previously [21]. The extension of our model to consider revenue impact of surgery management strategies during COVID-19 can provide further decision support to determine optimal strategies for postponement and resumption of surgeries in future scenarios.

### 5. Conclusion

We developed a 2-stage modelling framework for understanding elective surgery postponement patterns during a partial COVID-19 lockdown and the evaluation of alternative resumption strategies across multiple important operational outcome measures. The effective management of 34,025 unique cases over 43 operating rooms (ORs) and 18 surgical disciplines required an integrated systems approach across the operations of the entire hospital. The complexity of health systems coupled with the possibility of COVID resurgence underscores the

**Table A1**  
Top 10 surgeries in Cluster 1 and 2.

Procedure Code	Cluster	Description
SJ802T	1	Thyroid, Various Lesions, Hemithyroidectomy/Partial Thyroidectomy
SI725U	1	Uterus/cervix, Hysteroscopy, Diagnostic, D&C
SF820A	1	Abdominal Wall, Inguinal/Femoral Hernia, Bilateral Herniorrhaphy (MIS/open)
SH830P	1	Prostate Gland, Various Lesions, Radical Prostatectomy (MIS/open)
SM705T	1	Tonsils, Various Lesions, Removal with/without Adenoidectomy
SA702S	1	Skin and Subcutaneous Tissue, Tumor/Cyst/Ulcer/Scar, Excision biopsy, Lesion size more than 15 mm in diameter
SJ803T	1	Thyroid, Various Lesions, Total/Subtotal Thyroidectomy
SM714N	1	Nose, Various Lesions (turbinates), turbinectomy/turbinoplasty/Submucous Resection (with or without endoscopes)
SH835P	1	Prostate Gland, Various Lesions, Saturation Prostate Biopsy
SM724N	1	Nose, Various Lesions, Septoplasty/Submucous Resection
SB810K	2	Knee, Various Lesions, Primary Total Joint Replacement (Unilateral), open/MIS/navigated
SF819A	2	Abdominal Wall, Inguinal/Femoral Hernia, Unilateral Herniorrhaphy (MIS/open)
SB716K	2	Knee, Various Lesions, Primary Total Joint Replacement (Unilateral) with augmentation, requiring extra implants or bone grafts, open/MIS/navigated
SF801G	2	Gallbladder, Various Lesions, Cholecystectomy (open or lap)
SA824B	2	Breast, Tumor (malignant), Simple Mastectomy with Axillary Clearance, with/without Sentinel Node Biopsy
SA827B	2	Breast, Tumor (malignant), Simple Mastectomy with Sentinel Node Biopsy/Axillary Node Sampling
SG700U	2	Ureter, Cystoscopy and insertion of double J stent
SF701C	2	Colon, Anterior Resection (OpenMIS)
SC701L	2	Lung, Various lesions, Pneumonectomy/Lobectomy, MIS
SG800U	2	Ureter, Ureteroscopy and lithotripsy
SF708B	3	Bile Duct, Endoscopic Retrograde Cholangiopancreatography (ERCP) with sphincterotomy/removal of stone/insertion of biliary stent
SD812H	3	Heart, Coronary Disease, Coronary Artery Bypass Graft (Open)
SB808S	3	Spine, Deformities, Corrective Osteotomy – With/Without Computer Navigation
SF803C	3	Colon, Various Lesions, Right/Left Hemicolectomy (MIS/open)
SD712B	3	Blood vessels, Vascular System, Various Lesions, Insertion of Tenckhoff Catheter
SD731H	3	Heart, Valve (Repair/Replacement) - 1 Valve
SF702C	3	Colon, Colonoscopy (diagnostic), fiberoptic with/without biopsy
SB729S	3	Spine, Various Lesions, Decompression, Spinal Instrumentation, Multiple Levels
SD721A	3	Artery, Stenosis/Occlusion, Percutaneous Transluminal Angioplasty (PTA), Simple
SF813L	3	Liver, Various Lesions, Partial Lobectomy/Segmental Resection (open or lap)
SA811S	4	Skin and Subcutaneous Tissue, Deep greater than 3 cm/ Extensive Contaminated Wound, Debridement
SF701I	4	Intestine/Stomach, Upper GI endoscopy with/without biopsy
SD720A	4	Artery, Stenosis/Occlusion, Percutaneous Transluminal Angioplasty (PTA), Difficult (eg subintimal PTA, below knee PTA)
SG713B	4	Bladder, Cystoscopy, with or without biopsy
SA853S	4	Skin and Subcutaneous Tissue, Wound, Debridement < 3 cm
SF808A	4	Abdominal Cavity, Various Lesions, Exploratory Laparotomy (MIS/open)
SD821A	4	Artery, Various Lesions, Arterio-venous Fistula Creation
SK708B	4	Brain, Intracerebral Tumor, Biopsy and/or Decompression/Removal via Craniotomy, Complex
SF807E	4	

**Table A1 (continued)**

Procedure Code	Cluster	Description
SF809P	4	Esophagus/Intestine/Stomach, Upper GI endoscopy with insertion of Prosthesis (e.g. insertion of Celestin Tube/ complicated Polypectomy) Pancreas, Various Lesions, Whipple Operation/Total Pancreatectomy

importance of leveraging on advanced techniques in systems engineering and predictive analytics deployed in a user-friendly and adaptable platform for agile evidence-based decision making.

**Summary Table**

**What was already known on the topic**

- Surgeries reduced to cope with COVID-19 in hospitals should be resumed in a calibrated phased manner.
- Triaging and rationing of cases during COVID-19 and subsequent resumption of case should consider multidisciplinary approaches that considers patient, surgical and organizational factors.
- Process for guiding the phased reopening can be derived from a data-driven approach through the use of mathematical modelling and simulation approaches.

**What this study added to our knowledge**

- The development of a 2-stage modelling framework that leverages on a DES model with cluster analysis to understand the elective postponement patterns and evaluate the best phased resumption strategy.
- The proposed model enables the evaluation of alternative strategies accounting for OR utilization, waiting times to surgeries and clearance times for backlogs.
- The modelling framework leverages on machine learning and simulation model implemented within an interactive user interface for decision support showed that a calibrated phased approach can result in better outcomes across OR utilization, waiting times to surgeries and clearance times for backlogs. The user interface also provides visibility on the downstream projected bed demands under various scenarios.

**CRedit authorship contribution statement**

**HRBA, SSWL, ABY, AP, DBM, THK and MEHO:** were responsible for the conceptualization of the study. **SSWL, HRBA, and ABY:** did the literature review, data curation, formal analysis and investigation. **SSWL, HRBA, ABY, NHLN, and THK** assisted with the methodology and resources. **HRBA, SSWL, and ABY:** drafted the manuscript. **SSWL, ABY and HRBA:** contributed with review and editing of the final manuscript. **MEHO:** provided supervision, writing review and funding acquisition.

**Declaration of Competing Interest**

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Apart from the research grant, the authors declare that they have no other competing interest.

**Availability of data and materials**

Updated data and model results are available on <http://hi-board>.

[ap-southeast-1.elasticbeanstalk.com/](http://ap-southeast-1.elasticbeanstalk.com/). Username and password to access this site can be made available upon request to the Corresponding Author.

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### Authors' contributions

The work presented here was carried out in collaboration amongst all authors. HRBA, SSWL, ABY, AP, DBM, THK and MEHO were responsible for the conception and study design. SSWL, HRBA, and ABY did the literature review, modeling, and data analysis. SSWL, HRBA, ABY, NHLN, and THK under-took the literature review, contributed to the domain understanding and data acquisition. HRBA, SSWL, and ABY drafted the manuscript. SSWL, ABY and HRBA made significant revisions. SSWL, HRBA, THK and MEHO supervised the analysis, modeling and interpretation of data. THK, DBM and MEHO supplied valuable improvement suggestions to the analysis and the manuscript. MEHO is the principal investigator of the overall NMRC grant which provided the funding for this research.

### Ethics approval and consent to participate

The study protocol was not required for review by the Centralized Institutional Review Board of the Singapore Health Services (opinion date 26 May 2020, number 2020/2470) as it is a service evaluation project to advise policy through whole systems modeling with existing data and novel modeling methods leading to measured policy responses using deidentified data.

### Appendix A

See Table A1.

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