A Model to Create an Efficient and Equitable Admission Policy for Patients Arriving to the Cardiothoracic ICU*

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Objective: To develop queuing and simulation-based models to understand the relationship between ICU bed availability and operating room schedule to maximize the use of critical care resources and minimize case cancellation while providing equity to patients and surgeons.

Design: Retrospective analysis of 6-month unit admission data from a cohort of cardiothoracic surgical patients, to create queuing and simulation-based models of ICU bed flow. Three different admission policies (current admission policy, shortest-processing-time policy, and a dynamic policy) were then analyzed using simulation models, representing 10 yr worth of potential admissions. Important output data consisted of the "average waiting time," a proxy for unit efficiency, and the "maximum waiting time," a surrogate for patient equity.

Setting: A cardiothoracic surgical ICU in a tertiary center in New York, NY.

Patients: Six hundred thirty consecutive cardiothoracic surgical patients admitted to the cardiothoracic surgical ICU.

Interventions: None.

Measurements and Main Results: Although the shortest-processing-time admission policy performs best in terms of unit efficiency (0.4612 days), it did so at expense of patient equity prolonging surgical waiting time by as much as 21 days. The current policy gives the greatest equity but causes inefficiency in unit bed-flow (0.5033 days). The dynamic policy performs at a level (0.4997 days) 8.3% below that of the shortest-processing-time in average waiting time; however, it balances this with greater patient equity (maximum waiting time could be shortened by 4 days compared to the current policy).

Conclusions: Queuing theory and computer simulation can be used to model case flow through a cardiothoracic operating room and ICU. A dynamic admission policy that looks at current waiting time and expected ICU length of stay allows for increased equity between patients with only minimum losses of efficiency. This dynamic admission policy would seem to be a superior in maximizing case-flow. These results may be generalized to other surgical ICUs. (*Crit Care Med* 2013; 41:414–422)

Key Words: bed flow; cardiothoracic surgery; critical care; health care reform; modeling; queuing theory

The United States spends a significant portion of gross domestic product on health care (1). Occupying a large portion of this are ICU expenditures, which account for approximately 90 billion annually (2). This comes at a time when debt to gross domestic product ratio approaches unsustainability and health care costs must be contained. Although our aging population increases the need for critical care resources (3), the total number of ICU beds is decreasing (4) resulting in overcrowding. The average occupancy in a hospital ICU now ranges 77% to 90% (2). As hospital margins decrease, there will be increased pressure to use ICUs efficiently.

These issues are particularly important for cardiothoracic surgical patients. The ICU is a bottleneck to the cardiac operating room (OR), limiting the number of cases the system accommodates (3). When the ICU is poorly managed, there is high ICU occupancy, increased length of stay (LOS), and case cancellation, all of which harm cardiothoracic surgical programs (4–7).

* See also p. 662.

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The authors have not disclosed any potential conflicts of interest.

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DOI: 10.1097/CCM.0b013e31826a44d7

Case cancellation has multiple negative downstream effects (8). Foremost, cancellation delays necessary treatment for patients (9–13). There are also direct and indirect costs to the hospital associated with cancellation (14). Direct costs are reimbursement losses from cancellation and costs of poor resource utilization (15, 16). Additionally, cancellation results in increased LOS, reducing margin (7, 17). Cancellation also results in frustration of staff and poor morale that result in absenteeism and turnover, combining to damage the fiscal health of the hospital (8, 18–21).

Because even the best-managed ICUs cannot always smoothly meet demands of the surgical schedules, alternative modalities should be explored (22, 23). Examples include better management of OR scheduling or increasing ICU capacity (24, 25). Accurate modeling of perioperative systems is an attractive option as it saves time and money over trial-and-error approaches (26, 27).

Queuing theory and computer simulation have been widely used during the past century to study complex systems (28, 29). Queuing models are regularly used in manufacturing, the airline industry, traffic engineering, and telecommunications to provide insight into performance improvement and resource allocation (30, 31). Computer simulation models are often used to model complex systems. Computer simulations mimic real-world behaviors and include stochastic effects such as the uncertainty in patient arrivals, LOS, and other events common to queuing models (29). Computer simulation and queuing theory are often used in conjunction to model complex operational problems (18).

There is a rich body of literature using operations research tools to study patient flow and capacity management in health care, including the ICU (19, 22, 32). Swenson (24) suggested the concept of "justice" to distribute ICU beds based on prognostic data. Other authors have suggested reserving beds exclusively for elective surgery patients under quota systems, allocating different numbers of beds to elective cases daily (8). De Bruin et al (25) used queuing theory to model flow of the emergency cardiac care chain (emergency room to coronary care unit to ward) and found the majority of rejections were from lack of beds downstream.

The methodology used in this study was queuing theory and computer simulation. The goal was to develop a queuing model to understand the relationship between ICU bed availability and OR schedule to maximize utilization of intensive care resources. Because the underlying queuing model is extremely complex, computer simulation was used to model the system.

For the purpose of this study, we sought to understand how intensivists, with no control over OR scheduling, could best use the ICU given a specified number of cases any given day. We created a model using queuing theory to create equitable and efficient uses of ICU resources for cardiothoracic surgeons performing varying procedures. We then tested three different admission policies in our model to find the best balance between equity and efficiency.

MATERIALS AND METHODS

We studied all admissions to the cardiothoracic surgical ICU (CTICU) of a large tertiary care center during a 6-month period. This is a 12-bed ICU that admits approximately 1,200–1,600 cardiothoracic surgical cases annually. These cases are scheduled on weekdays, based on surgical block time designated by the cardiothoracic surgical department. Only occasionally are emergency cases done on weekends. For this study, emergency cases and readmissions were not considered as they represent an insignificant source of admissions and that data were not available. During this time period, there was no closure of ICU beds for any purpose (i.e., staffing, maintenance).

A typical day in this CTICU begins with the intensivist rounding on patients, determining which ones are dischargeable from the CTICU. The intensivist is given a list of surgical cases for a particular weekday the night before to have a sense of case volume the next day. When daily surgical volume exceeds the number of available beds in the CTICU, case cancellation occurs. This decision as to which cases are cancelled is complex and remains the discretion of the cardiac surgical team with no specified criteria or protocols. For the purpose of this study, we describe this process as highly complex provider determined and beyond the scope of this study.

Data were collected retrospectively as part of the unit's regular review of throughput. Percent occupancy was collected monthly as part of the hospitals monthly census data. The LOS was calculated as (discharge date) − (admission date). In addition, we collected the number of each type of surgeries and grouped them into categories based on expert opinion of expected ICU LOS at this institution (**Appendix 1**). This research is exempted from Institutional Review Board approval because all data were collected in a manner that subjects could not be identified.

Understanding Queuing Theory

Queuing models depend on precise measurements of three variables: arrival rate, service time, and number of servers in the system. For simple queuing systems, the arrival rate is modeled through a probability distribution of time between arrivals of two separate jobs. However, in this setting, arrivals represent surgical requests that arrive to intensivists each weekday as batch assortments of cardiothoracic surgery requests. The number of requests and mix of requests among cardiothoracic surgery types are uncertain. Thus, we have a queuing system with stochastically sized batch arrivals where one batch arrives on each weekday.

In our model, we formulated the problem as a general decision process with the ICU beds as finite number of servers (12 beds) fed by the OR. The processing time (LOS for each surgery type) was allowed to follow different distributions based on our retrospectively collected data, and each distribution had a 1-day minimum. On days where too few beds were available to satisfy all requests, some requests were rejected from the system (i.e., case cancellation). The cancelled cases were then placed on the next day's OR schedule, as is the typical process in our institution. In the real world, occasionally patients are cancelled and go to another hospital, leaving the system. For the purpose of this model, we ignored that event as it is rare.

In queuing terminology, this model is denoted as a *G/G/s*-queuing model with batch arrivals and multiple customer classes. This means that we allow a general arrival rate distribution, a general service time distribution (LOS), and multiple servers. We also assumed that any ICU bed could be allocated to any surgery type. For the purpose of this study, we ignored emergency cases as they are rare and readmissions as they go to another ICU.

Such *G/G/s*-queuing models including batch arrivals and multiple customer classes are exceptionally difficult to solve in closed form (17). Therefore, to provide realistic representations of ICU workflow, a computer simulation model was constructed using Rockwell Arena 13.5 (Rockwell Automation, Wexford, PA). The decision of interest in our model is which cases should be approved for surgery and which should be canceled.

Performance Metrics Unique to the Model

Our model is unique in that it seeks to balance "equity" and "efficiency" in determining optimal ICU admission policy. For patients, equity means the system should not repeatedly reject the same type of patient (i.e., same type of surgery). For surgeons, equity means each surgeon should be able to perform surgeries based on their specialty without repeated cancellation; as a byproduct of this, the patients also receive equity. In our institution, surgeons typically perform one to two types of procedures exclusively. Our article, therefore, focuses on developing an optimal admission control policy for the ICU to minimize case cancellation (i.e., maximize efficiency) while still giving consideration to equity, given stochastic admission requests, batch arrivals, and a fixed capacity ICU.

For the purpose of evaluating our proposed admission policies, we introduce two important measures of waiting time, the average waiting time ($\bar{W}_j$) and the maximum observed waiting time ($\widehat{W}_j$) for each patient type $j = 1,\ldots,J$ (equivalently, the surgery types performed by a given surgeon). These waiting time measures form the basis of our performance metrics for efficiency and equity.

Waiting time is incurred when cases are canceled because patients must wait at least 24 hrs to return for surgery before entering the ICU. We calculate a "grand average" ($\bar{\bar{W}}$) of the waiting time across all patient types. The value $\bar{\bar{W}}$ represents an aggregate measure; thus, $\bar{\bar{W}}$ is a proxy for overall efficiency of the ICU.

In many cases, average values disguise the true performance of systems, particularly when equity is considered (33, 34). Therefore, we introduce a second waiting time measure, $\widehat{W}_j$, corresponding to maximum observed waiting time for a type-*j* patient. As cases are repetitively cancelled, maximum waiting time increases and inequity in admission to the ICU rises. Thus, $\widehat{W}_j$ provides a metric related to inequity being faced by individual patients. This gives us an indication of "worst-case" performance experienced by patients attempting to enter the CTICU. Similar to $\bar{\bar{W}}$, we define $\widehat{\widehat{W}}$ as maximum observed waiting time across all patient types.

Differing Admission Policies

In creating the model, we tested three different admission policies: the current admission policy, a shortest-processing-time (SPT) policy, and a dynamic admission policy, defined later. Because the current admission policy has no specified criteria or protocols, we mimic the current policy by using a modified random policy with patient prioritization after repeated cancelations. Under this policy, patients postponed repeatedly (four times in our analysis) are given priority admission for the first available ICU bed. Note that patients may still be postponed additionally if no beds are available, which matches current practice. Patients who have not been postponed repeatedly are selected arbitrarily. This policy is equivalent to the current policy in place where intensivists must deal with many competing concerns in assigning ICU beds, and no direct protocol is in place.

The second policy tested is based on the SPT rule. This rule, popular in manufacturing environments (35), gives jobs with the shortest processing time (i.e., short LOS) highest priority. The SPT rule has been proven to maximize throughput in deterministic environments and performs well in stochastic environments. However, it is optimal in only very limited real-world settings (36). The downside of the SPT rule is that it consistently rejects patients with long expected LOS. This policy could be considered as emphasizing efficiency at expense of surgeon and patient equity.

Finally, we created a dynamic policy that adjusts priority of surgery requests each day based on current waiting time for surgical requests, the type of surgery request, and a user-defined parameter, denoted as α_j for patient type *j*. Formally, the dynamic policy assigns a priority value (P_i) for each arriving surgical request *i* according to the formula:

$$P_i = \alpha_j(t-\tau), j = 1,\ldots,J$$

where *t* denotes the current day, and τ is initial arrival day for surgical request *i*. The surgical request with the largest P_i value receives the first available ICU bed, and beds continue to be assigned in order of decreasing P_i values until no more ICU beds are available. The dynamic policy has been shown to minimize average waiting time for jobs in simple queuing systems (37). However, theoretical results have not been proven for scenarios as complicated as considered here with batch arrivals and non-Poisson arrival processes.

The values α_j are user-defined parameters that effectively determine "weighting" of patient wait times for each case type *j*. These weightings can be chosen to reflect relative expense or relative negative consequences for having patients of different case types waiting for surgery. In our setting, we are concerned with providing equity among different case types. Therefore, we choose $\alpha_j, j = 1,\ldots,J$ to minimize average maximum waiting time, $\bar{W}_{max}$, across case types. By minimizing $\bar{W}_{max}$, we decrease the difference between case types with the longest

TABLE 1. Admissions Per Month by Surgical Category

	Monthly Admissions by Surgical Category						
Month	Total Admissions	Mitral Valve Admissions	Aortic Valve Admissions	Coronary Artery Bypass Grafting Admissions	Ascending Aortic Surgery Admissions	Major Thoracic Admissions	Cardiac Other Admissions
1	90	15	27	28	6	5	9
2	101	30	18	22	11	4	16
3	131	37	18	45	6	10	15
4	109	34	19	28	4	6	18
5	95	28	28	26	6	4	3
6	104	34	21	26	4	14	5

average waiting time and case types with shortest average waiting time. Such a metric is a common measure of inequity in the literature (38). In general, no analytical procedure exists to guarantee correct choice of minimizing $\alpha_j, j = 1,...,J$ values. We used a local search procedure to find values of α_j that minimize $\bar{W}_{max}$ (39). Note that the value of α_j is determined by the input data. Different ICU settings would require different α_j estimates based on historical data. However, the underlying model remains unchanged and the relative performance of the policies would be similar.

Statistical Analysis

The historical data indicated that the distributions of surgical requests in our arrival batches were non-Poisson and random; therefore, we used empirical distributions from our data on batch size composition for the purposes of our model. In addition, the data showed that our service time (ICU LOS) was nonexponential. For the LOS data, we used mixed empirical distributions to capture the tail of LOS distribution (40). For each surgery type, we ordered all LOS data points in ascending order and used the first 75% of the data to construct the empirical distribution. For the remaining 25% of data points, we used an exponential distribution to fit the data. This allowed us to model patients with extremely long LOS that may have been underrepresented in our empirical data.

Simulations to Determine Best Admission Policy. In our simulation experiment, we tested the simulation model for 100 replications for each admission policy. Each replication represented 3650 days or 10 yr of admissions into the CTICU. We then observed $\bar{W}_j$ and $\widehat{W}_j$ for each patient type j across all three admission policies during each replication of simulation.

To validate our queuing models, we performed several tests discussed here and in the Results section. We collected 6 months of LOS data for patients arriving in the CTICU. We then conducted simulation experiments to compare our simulation-generated outputs to output measures collected in practice such as ICU bed occupancy and rejection rates. Our simulation-generated outputs matched values collected in practice.

RESULTS

Input Data

There were 630 admissions to the ICU during the study period (**Appendix 2** summarizing patient admission data). **Table 1** gives the number of admissions per month as well as classifying the admissions per surgical category. Monthly average admission requests ranged 3.95 to 5.77 per weekday. The average monthly LOS ranged 2.26 to 2.63 days (**Table 2**). Individual LOS ranged 1 to 39 days. There were ten patients with an ICU LOS greater than 12 days. Of these five (50%) were in the cardiac other category, four (40%) in the aortic valve category, and one (10%) in the mitral valve category.

Efficiency Performance Metrics

Figure 1 denotes average waiting time for the three different admission policies with corresponding 95% confidence intervals for each admission policy. As mentioned, this corresponds to efficiency of the ICU and it reasons that the SPT policy would perform best. The results show our dynamic policy performs second best on this metric (0.4997 days), resulting in mean waiting times 8.3% below the SPT policy (0.4612 days) and 0.7% above the current policy (0.5033 days). The performance

TABLE 2. Average Bed Occupancies, Length of Stay, and Admissions by Month

Month	Percent Occupancy	Average Length of Stay (Days)	Average Admissions Per Weekday
1	92	2.63	3.95
2	85	2.47	4.52
3	81	2.58	5.77
4	93	2.33	4.91
5	82	2.26	4.48
6	77	2.28	4.68

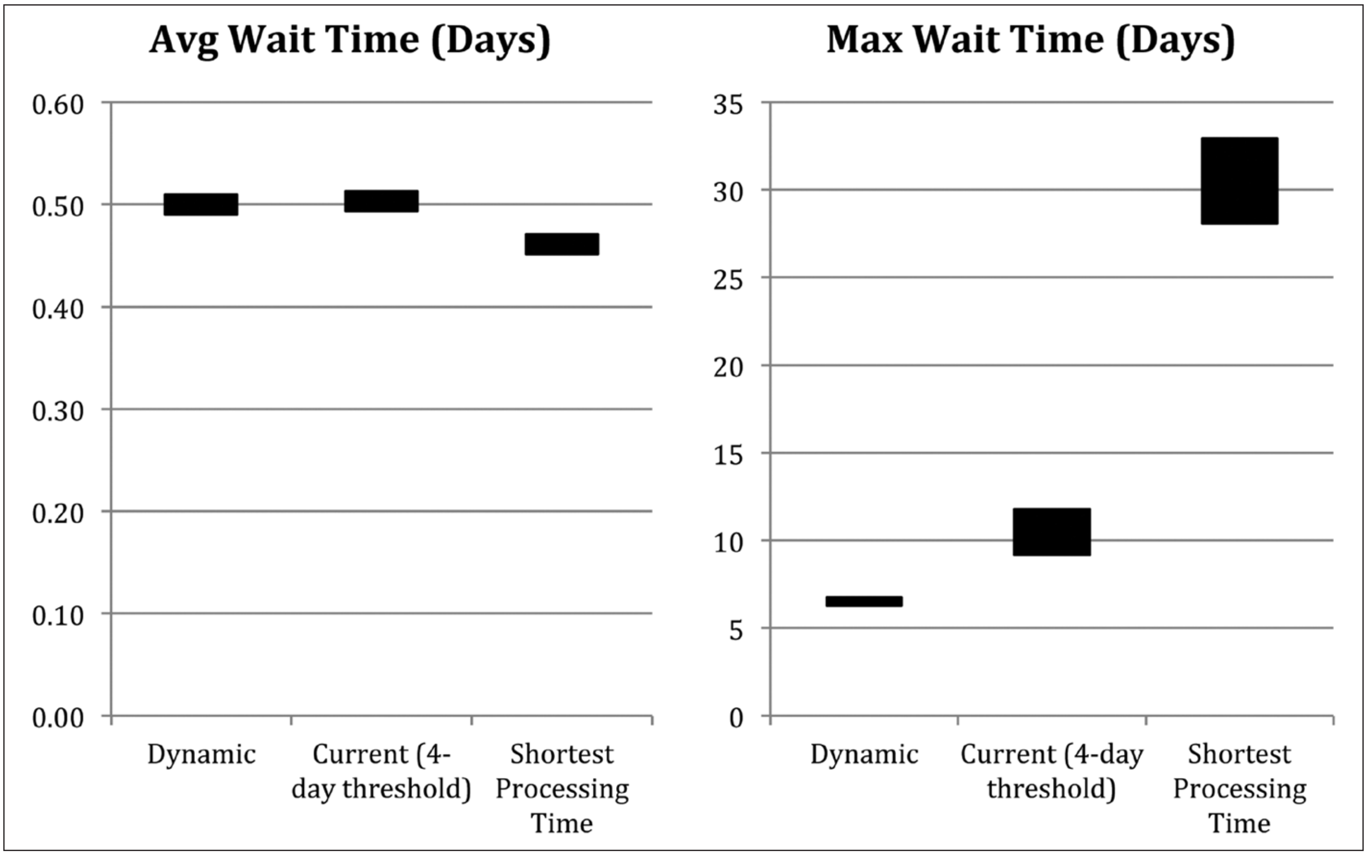

Figure 1. The chart on the left shows the average waiting time for the three different admission policies with corresponding 95% confidence intervals for each admission policy in our model. The chart on the right shows the maximum waiting time for the three different admission policies.

loss relative to the SPT policy represents the price the dynamic policy pays for equity. The efficiency loss of 8.3% represents a delay on average of 2 hrs. Because the minimum unit of time in our model represents 1 day, this increase is judged acceptable.

Figure 1 also displays maximum waiting times (and corresponding 95% confidence intervals) for the three different admission policies. This performance metric is a proxy for equity. On this metric, the dynamic policy performs 79% better than SPT policy and 38% better than the current policy. Our results suggest the dynamic policy could shorten the longest delay a patient would experience by 4 days compared with the current policy, and by almost 4 wk of waiting time compared to the SPT policy where patients are never reprioritized. This represents significant benefit to patients and providers.

Performance Metrics by Surgical Category

Figure 2 represents average waiting times for the different admission policies across six surgical categories. From Figure 2, the current policy results in average waiting times for surgery types between 0.4376 and 0.5215 days (range of approximately 2 hrs). Under the dynamic policy, average waiting times by case type have values between 0.3483 and 0.6204 days (range of approximately 6.5 hrs). Finally, under SPT policy, average waiting times vary by case type between 0.0400 to 1.5404 days (range of about 36 hrs). This is not unexpected; under SPT policy, the system repeatedly rejects surgeries with longest expected LOS. Because of this, it is not surprising that patients in the cardiac other group (i.e., ventricular assist devices) wait the longest.

This inequity becomes more profound when examining maximum observed waiting time for different surgery types (**Fig. 3**). The range of maximum observed waiting times are approximately 1.1 days, 3.0 days, and 28.6 days under the dynamic policy, current policy, and SPT policy, respectively. The SPT policy increases system efficiency at the cost of increasing inequity (particularly for surgery type cardiac other). The current policy increases equity by prolonging every surgery type at expense of efficiency. It is only the dynamic policy that effectively balances efficiency and equity.

In a clinical setting, the dynamic rule can be easily implemented using existing information technology systems or simple software (e.g., within Microsoft Excel) and inputting patient arrivals, departures, and surgical requests.

DISCUSSION

In the coming years, ICUs will become more heavily used and overcrowded as an aging population and fiscal deficits put increasing strain on our health care system. As hospitals face decreasing margins, there will be increased emphasis on proper uses of critical care resources and maximizing efficiency. Recently, unplanned surgical volume variation was

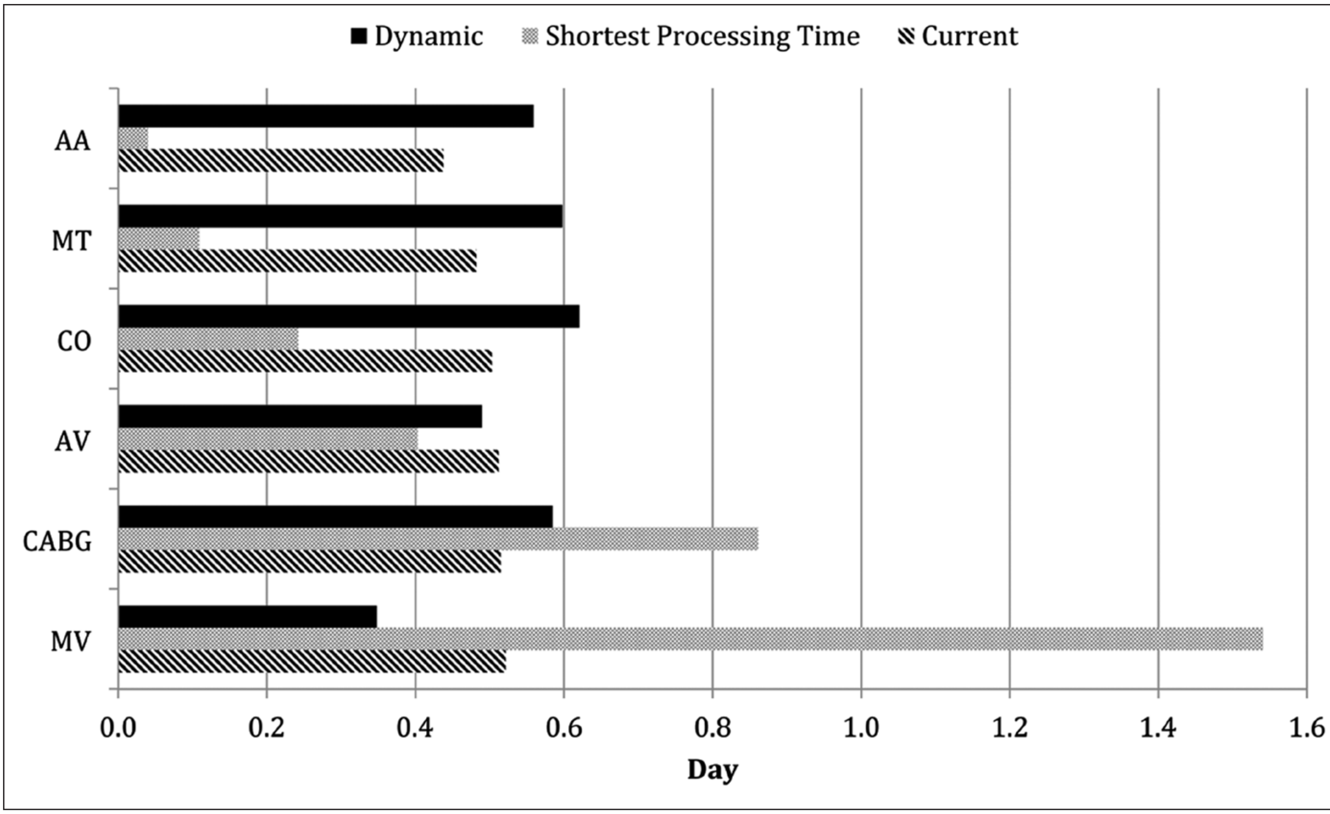

Figure 2. This clustered bar chart presents the average waiting time by case type under different admission policies. Under the shortest-processing-time policy, coronary artery bypass grafting (CABG), major thoracic (MT), and mitral valve (MV) patients receive higher priority while cardiac other (CO) and aortic valve (AV) patients wait due to their longer expected length of stay in ICU. AA = ascending aortic surgery.

shown to add to OR inefficiency (41). Because cardiothoracic ICU throughput is contiguous with the OR, it would reason that poor planning in the ICU could also increase surgical volume variation and lead to inefficiency. Complicating matters are that both surgeons and patients demand equity in any allocation process. This article focused on an admission policy for a cardiothoracic ICU with the goal of balancing efficiency and equity. It was taken from the point of view of intensivists faced with a set OR schedule attempting to make bed decisions, but could also be used by OR administrators at institutions lacking intensivists.

This 6-month experience illustrates that queuing theory and computer simulation can be used to model case flow through a cardiothoracic OR and ICU. To our knowledge, this is the only experience using a queuing model to look at different admission policies for an ICU contiguous with an OR based on functional ICU data that includes concerns related to equity. Consistent with findings from other applications in the literature, we find that equity is greatly increased with only small amounts of efficiency loss simply by explicitly considering equity concerns in policy decisions (42). These findings may be generalized to other surgical ICUs in which bed flow is directly related to OR scheduling. It may not be generalized to ICUs that function well below capacity or ICUs not downstream from the OR.

This article may have important practical implications. We found that a dynamic policy that effectively reprioritizes patients based on their current waiting times significantly outperforms static policies. However, we admit that our model setting is limited in that it used predominantly cardiac surgical patients with an arrival pattern based on case cancellation decisions at a single institution.

Note the current policy used in our simulation reprioritized patients after multiple cancellations. This is based on current practice, but it is not a codified procedure at this institution. Similar to many other ICU settings, workaround policies have been developed to respond to short-term capacity issues. If we were to remove this nonstandard reprioritization, the dynamic policy would provide even more significant savings. The dynamic policy has the additional benefit that it can be easily standardized and implemented using simple tools (e.g., a spreadsheet).

The strength of our argument comes from the large gain in preventable hospital days (i.e., the balance of equity and efficiency) seen when using a dynamic policy vs. competing policies. Together, Figures 1–3 show the dynamic rule results in large equity gains among patients and providers with limited losses in efficiency. Given the complexity of the cancellation process we studied and that our model has not been externally validated, our dynamic policy could be implemented only as a supplementary decision support tool for practitioners and administrators in other settings. As has been shown in other studies, overreliance on automated procedures can cause negative outcomes when input conditions change (43).

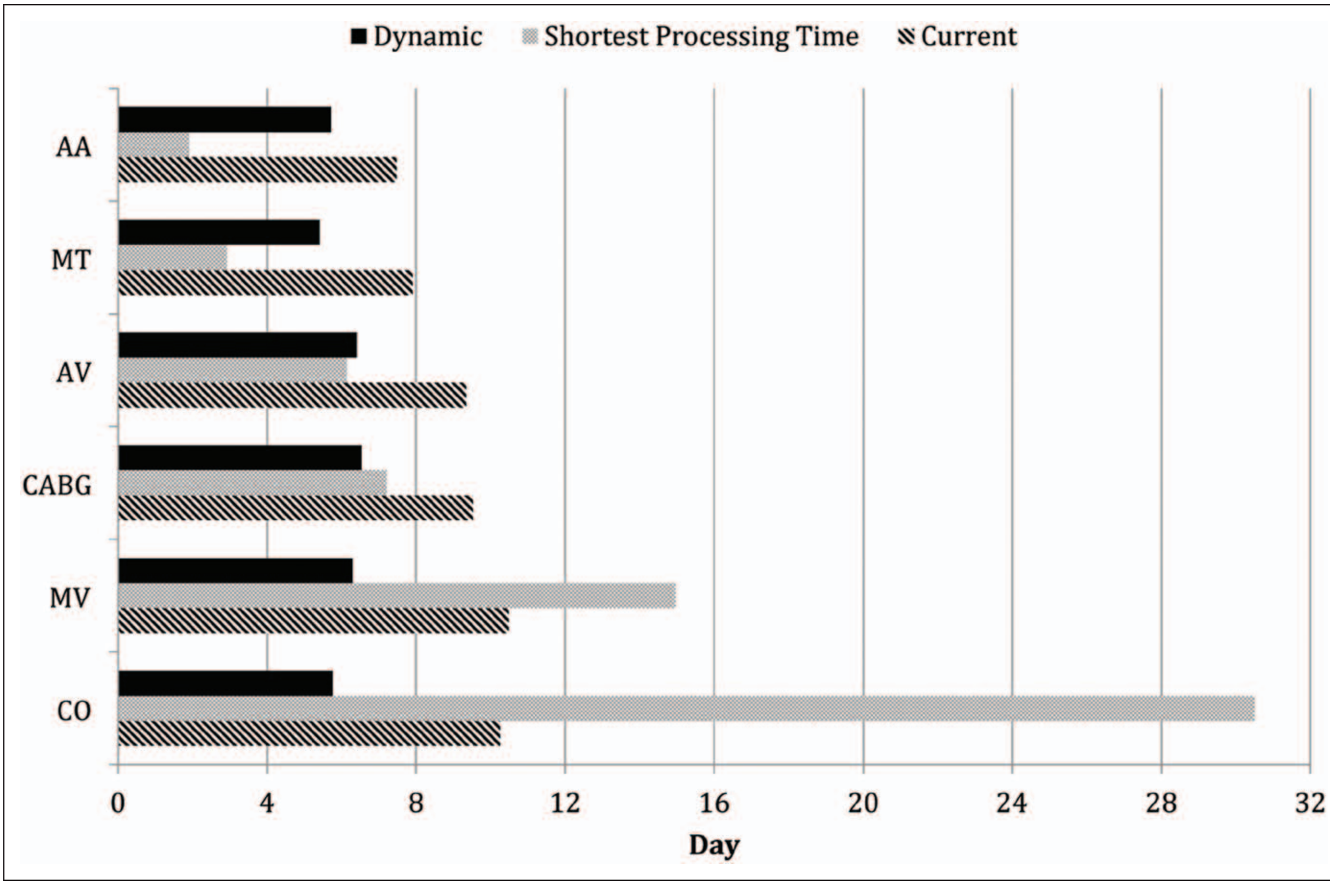

Figure 3. This clustered bar chart presents the maximum observed waiting time by case type. The average maximum waiting time can be as long as 10.5 days when the current rule is used, 30.5 days when the shortest-processing-time rule is used, and only 6.5 days when the dynamic rule is used. MV = mitral valve; AV = aortic valve; CABG = coronary artery bypass grafting; AA = ascending aortic surgery; MT = major thoracic; CO = cardiac other.

The introduction of automated decision-support systems in this setting can cause other challenges in terms of system design and garnering acceptance from users. A full discussion of this issue is outside the scope of this work, but related work is contained in (44) and (45). We must urge caution in extrapolating our exact results to other ICU settings, but we think this study demonstrates potential savings from tools such as queueing models and simulation in managing ICUs.

Finally, because ICU resources are limited, it is important to consider our arrival patterns. We found that our arrival patterns were non-Poisson, but highly random with large variability in the composition on batches day-to-day and week-to-week. Yet, for the most part, we were studying an elective OR schedule that was designated by the cardiothoracic surgery department. Certainly, creating a predictable and nonrandom OR schedule could greatly improve the capacity and bed flow of this ICU, potentially generating significant cost savings.

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APPENDIX 1. SURGICAL CASE CLASSIFICATIONS

Surgery Groups	Procedures
MV	1. MV repair/replacement 2. MV repair/replacement with CABG
AV	1. AV replacement 2. AV replacement w/CABG 3. AV replacement/MV replacement/tricuspid valve replacement
CABG	1. CABG
Ascending aortic surgery	1. Bentall procedure 2. Aortic arch aneurysm surgery 3. Ascending aortic aneurysm surgery 4. Elephant trunk stage I
Major thoracic	1. Pneumonectomy 2. Esophagectomy 3. Thymectomy 4. Complex lobectomy
Cardiac other	1. Atrial myxoma resection 2. Myocardial resections 3. Pulmonary embolectomy 4. Atrial septal defect resection 5. Orthotopic heart transplants 6. Insertion of ventricular assist devices 7. Admissions from outside institutions for computer tomography surgery

MV = mitral valve; AV = aortic valve; CABG = coronary artery bypass grafting.

APPENDIX 2. PATIENT PROFILE BY SURGICAL CASE CATEGORY

	Surgical Category					
	Aortic Valve	Ascending Aorta	Coronary Artery Bypass Grafting	Major Thoracic	Mitral Valve	Cardiac Other
Average age	68	59	65	69	58	57
Maximum age	92	82	91	86	85	85
Minimum age	24	20	35	20	21	18
Mortality rate	3.97%	3.23%	1.67%	0.00%	1.16%	7.14%
Day of surgery request						
% Monday	13.45%	35.71%	21.89%	19.35%	27.17%	29.85%
% Tuesday	25.21%	10.71%	18.34%	25.81%	30.06%	13.43%
% Wednesday	29.41%	14.29%	21.89%	38.71%	5.78%	11.94%
% Thursday	12.61%	10.71%	15.38%	6.45%	23.70%	26.87%
% Friday	19.33%	28.57%	22.49%	9.68%	13.29%	17.91%