Evaluation and Implementation of a Just-In-Time Bed-Assignment Strategy to Reduce Wait Times for Surgical Inpatients

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Abstract

Early bed assignments of elective surgical patients can be a useful planning tool for hospital staff; they provide certainty in patient placement and allow nursing staff to prepare for patients' arrivals to the unit. However, given the variability in the surgical schedule, they can also result in timing mismatches—beds remain empty while their assigned patients are still in surgery, while other ready-to-move patients are waiting for their beds to become available. In this study, we used data from four surgical units in a large academic medical center to build a discrete-event simulation with which we show how a Just-In-Time (JIT) bed assignment, in which ready-to-move patients are assigned to ready-beds, would decrease bed idle time and increase access to general care beds for all surgical patients. Additionally, our simulation demonstrates the potential synergistic effects of combining the JIT assignment policy with a strategy that co-locates short-stay surgical patients out of inpatient beds, increasing the bed supply. The simulation results motivated hospital leadership to implement both strategies across these four surgical inpatient units in early 2017. In the several months post-implementation, the average patient wait time decreased 25.0% overall, driven by decreases of 32.9% for ED-to-floor transfers (from 3.66 to 2.45 hours on average) and 37.4% for PACU-to-floor transfers (from 2.36 to 1.48 hours), the two major sources of admissions to the surgical floors, without adding additional capacity.

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1 Introduction

Hospital inpatient bed assignment is an intricate supply-and-demand process. As admissions occur throughout the day, clinicians place "bed requests" (or "bed orders") so that patients can be matched to a bed that fits their clinical needs ("bed assignment"). On the other hand, bed managers heavily depend on clinical teams to learn which beds will become available as discharges occur. As they gather this information, bed managers must decide when to make patient-to-bed assignments in a timely fashion, an increasingly challenging task at large hospitals which regularly operate at or near maximum capacity.

In this work, we study the impact of two bed placement strategies on access to general care inpatient beds for surgical patients at a large academic medical center, Massachusetts General Hospital (MGH), which staffs over 1,000 beds. We study how proactive bed-assignment strategies can contribute to extended patient wait times for beds and how they can be modified, using manufacturing principles, to reduce patients' wait times for beds and thus reduce congestion in the Emergency Department (ED) and the Post-Anesthesia Care Unit (PACU), a high priority for a hospital whose operational bed occupancy consistently hovered above 90% at that time. Lastly, we estimate how this benefit is compounded when combining it with strategic changes in the care pathways of short-stay surgical patients.

1.1 Motivation

Data from 2015 showed how early bed assignments could lead to a timing mismatch between patient readiness to move and bed availability. Each morning, nursing staff would review the surgical planned admissions for the day and pre-assign patients to beds regardless of the timing of the surgical schedule. This reassured the teams that all incoming patients who needed a bed would get one by the end of the day and gave them time to assign specific staff to each patient. This process also allowed bed managers to make intricate bed assignments before the natural pressures of the day built up. Indeed, the bed assignment process is further complicated at this hospital since it has a large share of two-person semiprivate (i.e., shared) patient rooms, which adds the need to guarantee compatibility with a roommate's gender and infection precautions for each bed request. A bed was considered available for assignment if it was empty, or if the patient occupying it had been identified by nursing as "pending discharge," i.e., expected to be discharged at some point that day.

This practice frequently resulted in situations where post-operative patients were waiting for pre-assigned beds that were still occupied, while an equivalent bed was idle "waiting" for its pre-assigned patient to finish their perioperative course. Specifically, in 2015, pre-assigned beds in twelve units (314 surgical beds) were idle "waiting" for patients for a total of 11,181 hours or 466 bed-days, affecting 3,284 (53%) of post-operative patients waiting for a general care bed.

This analysis led us to propose a Just-In-Time (JIT) bed-assignment strategy. JIT aims to provide fabricated parts into assemblies only when they are ready, avoiding delivery before it is needed, sitting idle and gathering inventory costs [34]. We hypothesized that an assignment process in which managers know the list of expected admissions for the day, but only assign patients to beds closer to the time in which they are ready to transfer, and only to beds that are ready to receive them, would reduce wait times. This is similar to the concept of delayed differentiation in manufacturing: by postponing the differentiation of a product for a specific customer until the latest possible point in the supply network, companies have been able to deliver more highly customized products and services more quickly [13].

At that time, hospital leadership was considering implementing a different patient flow strategy to increase access to beds and reduce upstream congestion: surgical short-stay elective patients (SSE), those who typically require at most 23 hours of post-procedure recovery, would recover overnight in the PACU by default (instead of on a general care floor) unless the patient's care team deemed that they required an extended stay, in which case they would be transferred to a general care floor. (Note that SSE patients have their case booked under a separate booking category to distinguish them from other scheduled surgical patients.)

We hypothesized that layering a JIT bed assignment on top of this change in patient flow would help to make the best use of the additional available beds. Finally, we also proposed to pool units of clinically similar floors, increasing the availability of potential beds patients that could go to as their bed requests were placed. To gauge the benefits of each strategy and motivate hospital leadership for a potential implementation, we built a detailed discrete-event simulation that emulated the bed-assignment process and bed occupancy in four high-volume surgical floors that could serve as a model for implementation across the rest of the surgical floors.

1.2 Literature Review

The practice of pre-assigning patients to beds is relatively common in the operations research literature. In fact, the majority of literature on optimizing patient-to-bed assignments designates elective patients to beds with a significant lead-time: some pre-assign beds for the upcoming weeks assuming patients' length-of-stay to be known beforehand [2, 5, 6, 11, 32], while others do so the day before patients are scheduled to arrive [7, 8, 45]. Multiple studies propose deciding on patient-to-bed assignments at multiple, specific times each day [15, 23, 35, 33], most of which truly study a real-time setting, where assignments are made instantaneously when and only when both patient and bed are ready. In terms of their applicability to practice, several of these studies [2, 6, 7, 8, 11, 32, 45] test their developed methodology with computer simulations, while others [5, 15, 23, 35, 33] test on data from actual hospitals. Only Thomas et al. [39] and Thompson et al. [40] report on actual implementations. In both cases, at Mount Sinai Medical Center (a 1171-bed tertiary care teaching hospital), and at Windham Hospital (a 130-bed acute care community hospital), assignments were decided periodically—every hour [39] or every eight hours [40]—for multiple patients and beds simultaneously.

Systematic changes to the bed-assignment process are not as common in the clinical literature. Research in this area typically focuses on process improvement efforts to streamline the bed-request process, particularly for newly admitted patients from the ED. These efforts include increasing collaboration between stakeholders to reduce rejections [37], having a direct involvement from leadership [29], or increasing data transparency [9, 10, 21]. Most clinical work related to decrease wait times in upstream locations focuses on different mechanisms to increase bed availability via increasing early-morning discharges or smoothing out discharges throughout the week [4, 21, 43, 41]. Other strategies include changing bed-demand patterns by optimizing the operating room schedules [12, 44] and changing intensive care unit capacity management strategies [26]. Finally, we note that there is a vast literature on the association between long wait times and worse patient outcomes, especially for patients in the ED (see [20] and references therein).

Regarding short-stay patients, standardized, separate care pathways are most commonly found within the ED. Patients who are expected to need monitoring for less than 23 hours are sometimes placed in highly protocolized ED Observation units, whose fiscal and patient flow benefits are well studied [3, 30]. In the surgical space, literature is not as vast, but focused pathways have been shown to decrease length-of-stay by increasing discharge efficiencies and increasing bed availability [42, 36].

Our work follows a similar approach taken by Hiltrop [16] who evaluated (though did not implement) a Just-In-Time bed-assignment policy together with early daily discharges in a set of units with private rooms only. In contrast, the units we focus on primarily have semi-private rooms (with cohorting requirements), and therefore we believed it was important to create a detailed simulation model given that the relative benefits of a JIT policy under cohorting restrictions are not clear *a priori*. To the best of our knowledge, there are no previous reports documenting the implementation of a real-time bed-assignment strategy which, coupled with changes in care pathways for short-stay patients, proved to be particularly effective at increasing access to general care floor beds.

2 Methodology

In this section we describe the bed request processes, the data sources that we used to build the simulation model, the metrics that we used to assess the effectiveness of our proposed interventions, and the simulation we used to test the proposed strategies. Note that this research was conducted under supervision of Mass General Brigham's Institutional Review Board (protocol `2011P001124`).

2.1 Bed Request Process

Bed requests to floors originate from five different sources: the Post-Anesthesia Care Unit (PACU, where patients recover from anesthesia after surgery), the ED, Intensive Care Units (ICUs), other inpatient floors, and "direct" admissions (non-operative scheduled admissions and hospital transfers). In the PACU there are mainly two types of patients who need beds: elective patients, who come from home for their surgery and need a "new" bed, and non-elective patients, who had been admitted to the hospital prior to surgery (mostly via the ED) and usually go back to the bed they were in before. It is the former group which creates the largest demand for surgical beds on non-holiday weekdays (see Table 1). Notably, all bed requests are generated based on a clinical team's assessment of a patient, except for elective surgical patients, whose bed requests are generated automatically upon checking in for surgery. It was the availability of these bed requests in the electronic medical record system early in the day that enabled the workflow of assigning beds to patients even if their surgery had not started yet.

We hypothesized that the use of a Just-In-Time (JIT) bed assignment would allow a timelier matching between bed demand and supply. To assess the potential effectiveness of this strategy, we initially focused our analysis on four high-volume, largely self-contained surgical floors at MGH: two floors specialized in General Surgery, Surgical Oncology, and Trauma and Emergency Surgery (with 36 and 27 beds), and two floors specialized in Orthopedics, the first of which also hosts Urology (with 36 and 30 beds). We built and validated a detailed patient flow simulation model of these floors and their bed-request interactions with the sources cited above.

2.2 Data

We linked seven data sets to build the patient flow simulation model:

1. *Bed requests*: contains all historical bed-request and -assignment timestamps, as well as pending-discharge timestamps;
2. *Surgical cases*: has patients' surgery information, including whether cases are elective and whether they are expected to be short-stay; it also contains relevant timestamps in the perioperative environment, including when patients arrived in the PACU, anesthesia recovery timestamps, and when they left the unit;
3. *Inpatient admissions, discharges, and transfers (ADT)*: contains all the timestamps that detail patient movement on the surgical floors of interest (and the rest of the hospital), including the time stamps of when a patient arrived in and left a specific bed;
4. *Bed cleaning*: has the time stamps of when beds were cleaned and thus were ready to receive the next patient;
5. *Bed closures*: contains information on when beds were closed and thus unavailable, including the reasons for closures (e.g., infection control in semiprivate rooms, maintenance, staffing);
6. *Patient infections*: clinical patient-level data which limits cohorting in semiprivate rooms; and
7. *Patient gender*: self-explanatory; also limits cohorting.

In 2015 there were 10,771 bed requests into the four surgical floors of interest (see Table 1): 6,204 from the PACU, 2,824 from the ED, 701 from ICUs, 180 transfers from other inpatient floors at MGH, and 862 "direct" admissions to the floors. While the simulation includes all calendar days in 2015, we restrict our analysis of several key metrics to non-holiday weekdays since these are the days in which elective surgical volume is highest and when the hospital is most congested. We note that SSE patients represented 7.2% of the average daily admissions on non-holiday weekdays during that time frame.

Table 1: Average daily patient admissions by source and time period

Source	Simulation (2015)		Pre		Post		Change, Pre vs. Post	
	Overall	Weekdays	Overall	Weekdays	Overall	Weekdays	Overall	Weekdays
PACU	17.00	23.40	16.34	22.92	16.52	22.44	0.18 [−1.96, 0.79]	−0.48 [−2.15, 1.14]
—non-SSE	*15.21*	*20.85*	*13.98*	*19.57*	*15.12*	*20.51*	*1.14* [−1.31, 1.94]	*0.94* [−0.81, 2.54]
—SSE	*1.79*	*2.56*	*2.37*	*3.35*	*1.40*	*1.93*	***−0.97*** [−1.60, −0.44]	***−1.42*** [−1.98, −0.62]
ED	7.74	7.15	6.80	6.53	7.84	7.53	**1.05** [0.09, 1.98]	1.00 [−0.05, 2.18]
Admissions	2.36	2.86	2.30	2.79	2.42	3.00	0.11 [−0.52, 0.57]	0.21 [−0.45, 0.82]
ICU	1.92	1.72	1.59	1.37	1.58	1.40	−0.01 [−0.40, 0.46]	0.03 [−0.51, 0.50]
Floor	0.49	0.51	0.41	0.43	0.21	0.24	−0.20 [−0.47, 0.04]	−0.19 [−0.46, 0.14]
Overall	29.51	35.64	27.44	34.04	28.57	34.60	1.13 [−1.23, 1.86]	0.56 [−1.36, 2.39]

Notes. "Weekdays" only includes non-holiday weekdays (Monday through Friday). "Pre" and "Post" denote the pre- and post-implementation periods, respectively. Confidence intervals shown are via an interrupted time series analysis; intervals which do not contain zero are bolded. Averages for PACU-source patients are shown overall as well as broken down into two mutually exclusive groups: SSE and non-SSE patients.

2.3 Metrics

We used the following performance metrics to gauge the impact of the proposed interventions:

(a) Patients' wait times for beds

(b) Beds' idle time

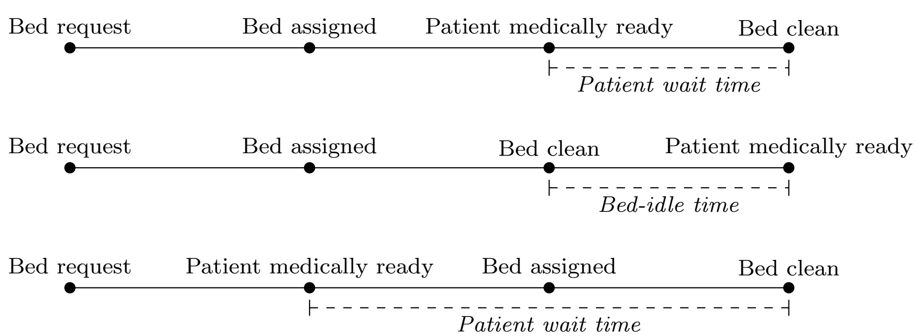
(c) Daily admissions to floors

(d) Operational bed occupancy

We define a patient's wait time for a bed as the interval between the moment a patient is medically ready to transfer until an assigned bed has been cleaned and is thus ready to receive the patient; this excludes hand-off and transportation times. This is the study's primary metric of interest as it is directly linked with quality of care and upstream congestion. Similarly, we define a bed's idle time as the period between when a clean bed is assigned to a patient until the time that patient is medically ready to transfer to the bed. A visual representation of these metrics is shown in Figure 1.

While (a) is the primary metric of interest, metric (b) allows us to capture how long beds are not physically occupied despite having already been assigned to a patient. This is a reflection of how well timed the bed-assignment process is. Suppose there are two similar patients that could go to the same ready-bed, with one of them still undergoing surgery while the second one is ready to transfer. If the bed is assigned to the former, the first patient will have a very short wait time, but the bed could sit idle potentially for a long time while both the latter patient's wait time and the bed's idle time could have been shortened. Formally, bed-idle time occurs when a ready-bed is assigned to a patient who is not medically ready to transfer. We measure both the sum of the total hours that beds were idle and the total number of such assignments per day.

Figure 1: Three example timelines of possible bed-assignment events, illustrating patients' wait time for beds and beds' idle time. In Examples 1 and 3, there is zero bed-idle time, while in Example 2, there is zero patient wait time.



The number of daily admissions, as the name suggests, reflects the total number of new patients that arrive in the four units of interest per day from different locations across the hospital. Finally, to calculate operational bed occupancy, we divide the 11:59pm total patient census on the four floors by the number of operational beds (physical capacity minus any closed beds). The two last metrics serve as a control, to dissect whether there were significant changes in bed supply and demand.

2.4 Simulation Model and Scenarios

In this section, we describe our simulation approach and the simulation scenarios we assessed; we describe the simulation validation and details on the patient flow modeling assumptions in the Supplementary Material. We used `python`'s `simpy` framework [38] to create a discrete-event simulation that emulated the bed-assignment process with historical data from 2015 and then modeled how patient wait times would change under a JIT bed-assignment process. This is a non-trivial task for several reasons:

i) historical bed-assignment rules were not standardized nor documented, i.e., while bed managers generally assigned beds to patients who had been waiting the longest, specific patients or specific areas of the hospital could be prioritized depending on the needs of the moment;

ii) 116 out of 129 beds (90%) in the four floors of interest are semiprivate, making modeling of bed closures, bed swaps (i.e., moving a patient to another bed in the same floor), and dynamic patient infection status critical to generate realistic results; and

iii) we had to link multiple data sources, some of which were not fully populated or not always easy to match.

Base scenario. In the base scenario, patients needed to be assigned to a bed on the same floor that they were historically assigned. Since the historical rules for prioritization were not standardized, the model prioritized patients for assignment based on the order that they were historically assigned. All patients could be assigned to "pending discharge" beds (beds in which the current patient is indicated as leaving at some time later that day), and bed assignments for elective surgical patients could begin as soon as their bed requests had been generated (i.e., before their surgeries).

JIT strategy. We modeled JIT by following the principle of "only ready patients can be assigned to ready beds." "Ready patients" means that patients are not considered for assignment to beds until they are deemed medically ready to leave the care area whence they are transferring to the floor. This is represented by the time of their bed request for all areas except the PACU. For the PACU, given that elective surgical patients' bed requests are generated before their surgical procedures begin, we consider these patients to be medically ready at the earliest of i) two hours after their arrival to the PACU (following surgery) and ii) the timestamp recorded by nursing indicating their medical readiness to transfer. The two-hour threshold was set by nursing and physician leaders, as the medical readiness timestamps were not reliably available for that period. "Ready beds" means that beds are available for assignment only after they become empty (not necessarily clean), and not when they are labeled "pending discharge."

Pooling strategy. In addition to JIT, we also evaluated the potential benefit of modifying the bed-assignment process through the use of *pooling* of floors, i.e., by increasing the flexibility with which a patient is assigned to specific floors (based on their clinical characteristics and needs). In general, rules dictating the placement of patients with various clinical characteristics to specific locations are not well-defined (hence the use of historical placement as noted above in the base scenario). Therefore, to assess the benefit of flexibility in patient placement, we grouped patients based on their clinical service and designated which of the four floors under consideration could be used to place such patients. These groupings (and differences relative to the previous assignment policies) can be described broadly in two groups:

(i) The two floors with patients from General Surgery, Surgical Oncology, and Trauma and Emergency Surgery could take any patient among those three clinical services. (In contrast, historically Trauma and Emergency Surgery patients went to only one of the two floors.)

(ii) The two floors with Orthopedics patients (one of which also has Urology patients) could take any Orthopedics or Urology patient (without any distinction based on type of surgery).

Short-stay reduction strategy. The last strategy we considered is a reduction in short-stay elective (SSE) patients who go to the floor after surgery, a change which hospital leadership was actively considering at the time. That effort focused on having SSE patients recover overnight in the PACU without requiring being sent to the floor (unless it was deemed clinically necessary by the patient's team). To model the SSE reduction we assumed that any SSE patient who historically stayed at least two days in the hospital would continue to go to the floor (i.e., request a bed as before). We also assumed that a random subset of the zero- and one-day LOS SSE patients no longer requested a bed; for present purposes, we focus on assuming a *50% reduction* in the number of such patients (we also conducted a detailed sensitivity analysis; see the Supplementary Material for additional description and results). We use the notation $\text{SSE}^{<}$ to denote this strategy.

All together, the four primary scenarios we evaluated are as follows:

1. JIT;
2. JIT+Pooling: JIT and pooling combined;
3. $\text{SSE}^{<}$; and
4. JIT+Pool+$\text{SSE}^{<}$: JIT, pooling, and $\text{SSE}^{<}$ combined, which corresponds with the actual implemented scenario.

2.5 Simulation Model Results

The results of the simulation model across the four scenarios are shown in Table 2. We describe the results for each scenario in turn. Throughout, we denote the α-quantile as Q_α, where $\alpha \in (0, 1)$.

JIT and JIT+Pooling scenarios

Under the JIT intervention, the model estimates decreases in average wait times for patients from all sources. This reduction is most notable for PACU patients, with an expected decrease in average wait time by 27.8%. While not adversely compromising average wait times from other sources, the observed improvements are noticeably smaller, particularly for the ED (with a reduction of 1.3%). The median performance of the JIT+Pooling scenario is similar to JIT alone, with a slightly lower average overall patient wait time. The most notable difference, however, is for higher quantiles, where we observe a significant benefit of adding the pooling strategy. This suggests that the primary benefit of pooling (i.e., increasing flexibility in terms of patients' assignments to units) is for patients with historically longer wait times for whom alternative placements might be possible. In practice, patients with exceptionally long wait times might have their possible unit assignments manually adjusted on an *ad hoc* basis (with clinical input and in order to avoid further delays); in contrast, using a pooling strategy can potentially decrease the need for such workarounds by strategically articulating and incorporating such placement priorities into the normal bed assignment process, thereby reducing long waits.

Table 2: Simulation results for patients' waits for beds (in hours) for various interventions

Source	Intervention	Average		$Q_{0.5}$		$Q_{0.75}$	
		Value (SE)	Δ_R	Value (SE)	Δ_R	Value (SE)	Δ_R
PACU	Base	2.59 (0.000)		0.00 (0.000)		2.34 (0.002)	
	JIT	1.87 (0.000)	−27.8	0.18 (0.001)		1.68 (0.002)	−28.5
	JIT+Pool	1.76 (0.002)	−32.0	0.02 (0.001)		1.37 (0.002)	−41.4
	SSE$^<$	2.54 (0.001)	−2.2	0.00 (0.000)		2.16 (0.004)	−7.7
	JIT+Pool+SSE$^<$	1.58 (0.003)	−39.2	0.00 (0.000)		1.20 (0.003)	−49.0
ED	Base	3.57 (0.001)		1.12 (0.002)		4.22 (0.004)	
	JIT	3.52 (0.001)	−1.3	1.05 (0.001)	−5.8	3.79 (0.004)	−10.2
	JIT+Pool	3.53 (0.005)	−1.2	0.94 (0.003)	−15.5	3.87 (0.009)	−8.3
	SSE$^<$	3.46 (0.002)	−3.1	1.04 (0.002)	−6.9	4.06 (0.008)	−3.8
	JIT+Pool+SSE$^<$	3.33 (0.004)	−6.8	0.88 (0.003)	−21.5	3.42 (0.013)	−19.0
Admissions	Base	10.59 (0.002)		3.71 (0.007)		11.28 (0.012)	
	JIT	9.65 (0.002)	−8.8	2.61 (0.004)	−29.5	10.87 (0.011)	−3.6
	JIT+Pool	9.67 (0.006)	−8.7	2.48 (0.007)	−33.0	11.06 (0.030)	−1.9
	SSE$^<$	10.49 (0.004)	−1.0	3.68 (0.012)	−0.6	10.90 (0.019)	−3.4
	JIT+Pool+SSE$^<$	9.39 (0.007)	−11.3	2.35 (0.006)	−36.6	10.36 (0.046)	−8.2
ICU	Base	26.85 (0.003)		21.31 (0.020)		35.45 (0.021)	
	JIT	25.51 (0.002)	−5.0	18.85 (0.015)	−11.5	33.93 (0.012)	−4.3
	JIT+Pool	25.68 (0.012)	−4.3	18.70 (0.055)	−12.2	34.70 (0.034)	−2.1
	SSE$^<$	26.64 (0.007)	−0.8	20.79 (0.029)	−2.4	35.33 (0.030)	−0.3
	JIT+Pool+SSE$^<$	25.27 (0.013)	−5.9	17.68 (0.059)	−17.0	34.37 (0.031)	−3.1
Floor	Base	9.08 (0.005)		2.75 (0.015)		5.77 (0.017)	
	JIT	8.35 (0.003)	−8.0	2.18 (0.010)	−20.7	5.25 (0.016)	−9.1
	JIT+Pool	8.45 (0.022)	−6.9	1.80 (0.017)	−34.4	4.88 (0.019)	−15.4
	SSE$^<$	8.93 (0.010)	−1.6	2.69 (0.018)	−2.1	5.67 (0.029)	−1.8
	JIT+Pool+SSE$^<$	8.31 (0.019)	−8.4	1.62 (0.019)	−41.0	4.66 (0.028)	−19.3
Overall	Base	4.76 (0.000)		0.54 (0.001)		4.05 (0.002)	
	JIT	4.13 (0.000)	−13.3	0.64 (0.001)	18.8	2.82 (0.001)	−30.4
	JIT+Pool	4.07 (0.002)	−14.6	0.49 (0.002)	−10.2	2.50 (0.004)	−38.3
	SSE$^<$	4.76 (0.001)	0.0	0.48 (0.002)	−11.8	3.96 (0.003)	−2.2
	JIT+Pool+SSE$^<$	3.94 (0.002)	−17.2	0.42 (0.001)	−22.0	2.32 (0.003)	−42.6

Notes. Relative (percentage) change, denoted Δ_R, is calculated relative to the base scenario. Standard errors for estimates are indicated "(SE)" and are shown next to the relevant value; all results shown are averaged across 100 simulation runs. SSE$^<$ models a 50% reduction in demand for beds from zero- and one-day-LOS SSE patients.

Reductions in SSE volume

In the historical period, SSE patients account for approximately 10.5% of those from the PACU. Not surprisingly, reducing overall demand for inpatient beds leads to decreases in waits for beds across all areas, especially in the PACU (although the overall average is unchanged, as SSE patients have the smallest average wait time at baseline). However, this decrease is modest in comparison to the relative improvements under the JIT scenario; for example, PACU patients' average wait decreases 2.2% in SSE$^{<}$ versus 27.8% with JIT. The only area where this behavior is not observed is for the ED (JIT corresponds to a 1.3% reduction in the average, whereas SSE$^{<}$ is 3.1%). This is likely due to the fact that the ED is the second largest source of surgical bed requests (after the PACU), and therefore ED patients benefit directly from reduced demand for the relevant beds.

Note that SSE$^{<}$ assumes a 50% reduction in zero- and one-day LOS SSE patients. We also conducted a detailed sensitivity analysis (see Supplementary Material); even in the most extreme SSE reduction scenario (100% reduction in such patients), the change in wait times (on average, median, and at other quantiles) is still modest in comparison to the effect from JIT+Pooling, highlighting the relative benefit of the latter as a strategy to reduce wait times without the need to develop alternative care pathways for patients to (non-inpatient) locations.

Combined JIT+Pooling and SSE reductions

Table 2 clearly demonstrates the potential synergistic effects of an assignment policy such as JIT and bed pooling in combination with a strategy to reduce the need for inpatient beds (as captured by SSE reductions) across all sources. We note the importance of considering the joint impact of these different interventions as their effect is not necessarily additive and the *a priori* relative benefits is not obvious.

Changes in other metrics

In the Supplementary Material (Table SM3), we also show the changes in the various scenarios for bed-idle time and occupancy. While occupancy is generally comparable across the various proposals (around 86-89%), the bed-idle time decreases substantially, from an average of 54.6 idle hours per day to 7.8 hours per day in the JIT+Pooling+SSE$^{<}$ scenario, representing an 85.8% reduction. We see that such large reductions occur in all the scenarios with JIT present, confirming that the JIT assignment mechanism is able to decrease the amount of time that ready beds are assigned to patients who are not yet medically ready to transfer into them. While this idle time is not directly tangible, it complements the patient-centric wait time measure as an alternative view of system (in)efficiency in the bed assignment process.

3 Implementation

On January 30, 2017, SSE patients started recovering fully in the PACU and were assigned an inpatient bed only if explicitly requested post-operatively due to clinical needs. With this intervention, the number of SSE patients being admitted to a surgical inpatient bed decreased from 3.35 on average per non-holiday weekday to 1.68, a 50%

reduction. JIT bed assignment and pooling were implemented in the four units of interest a few weeks later, on February 27, 2017.

To assess the impact of the implementation of these strategies, we compare performance metrics on the four surgical floors of interest between two periods: a pre-implementation period (July 1, 2016 through January 29, 2017) and a post-implementation period (February 27, 2017 through May 14, 2017). Note that the pre-implementation period starts after a transition to a new electronic medical record at MGH, while the post-implementation period's end coincides with the expansion of the JIT bed assignment to other floors. For a table comparing patient volumes by source in these two periods, see Table 1.

3.1 Statistical Analysis

Surgical census tends to have highly specific patterns; it usually peaks mid-week and reduces significantly during weekends [31, 27, 44]. Consequently, patients' wait times, being highly dependent on inpatient occupancy, are not independent from one another (from one day to the next), and thus we cannot apply traditional independent-sample-based statistical procedures. Therefore, to generate confidence intervals for estimates of the average and various quantiles of wait times for weekday requests, we apply a stratified bootstrapping procedure, where the stratification is based on grouping requests at the weekly level. (Each week consists of requests placed from Monday through Friday of that week.)

To set notation, let W_{pre} and W_{post} denote the sets of weeks in the pre- and post-implementation periods, respectively. (We exclude the first week from the pre-implementation period given that it is a single day.). For every week $w \in W_{\text{pre}} \cup W_{\text{post}}$, we let D_w denote the patient wait times for all patients represented in week w. Using this setup, for each bootstrap replication $b \in \{1, 2, \ldots, B\}$, we perform the following:

1. We sample (independently, uniformly, and with replacement) from W_{pre} with size $|W_{\text{pre}}|$ to generate indices $i_1^*, i_2^*, \ldots, i_{|W_{\text{pre}}|}^* \in W_{\text{pre}}$. We do the same with W_{post} to sample indices $j_1^*, j_2^*, \ldots, j_{|W_{\text{post}}|}^* \in W_{\text{post}}$.
2. For the statistic S of interest (e.g., S is an average), we compute two statistics (an absolute version $\widehat{A}_b^S$ and a relative version $\widehat{R}_b^S$):

$$\widehat{A}_b^S := S\left(D_{j_1^*}, D_{j_2^*}, \ldots, D_{j_{|W_{\text{post}}|}^*}\right) - S\left(D_{i_1^*}, D_{i_2^*}, \ldots, D_{i_{|W_{\text{pre}}|}^*}\right),$$
$$\widehat{R}_b^S := S\left(D_{j_1^*}, D_{j_2^*}, \ldots, D_{j_{|W_{\text{post}}|}^*}\right) \Big/ S\left(D_{i_1^*}, D_{i_2^*}, \ldots, D_{i_{|W_{\text{pre}}|}^*}\right) - 100\%.$$

Following this procedure, we report bias-corrected confidence intervals for both the absolute changes A and the relative changes R. Note that for a given replicate b, we compute the statistic based on the *patient-level data* with frequency corresponding to the sample indices. We repeat this process for several choices of statistic S, including the average and quantiles Q_α, where $\alpha \in \{0.5, 0.75\}$. Consistent with standard practice, we set $B = 10^4$. All bootstrapping is conducted with the statistical language `R` and using the standard `boot` package.

There are several motivations for taking this bootstrapping approach as compared with other possible methodological choices. First and foremost, this approach makes full use of patient-level data. In particular, if we instead computed relevant statistics at the week level and *then* considered changes in those statistics, it would be difficult to assess changes for statistics which rely on a larger number of data points for reliable estimates, especially when considering analyses by individual source for which there may be fewer than 10 patients per week. The second advantage of this approach is that while wait times within a given day or on adjacent days are not independent, the high turnover rate of surgical floors (and exclusion of requests on weekends) supports an argument for conditional independence of wait time statistics *across weeks*. As a partial validation of our approach, we examined the mean and quantiles as above when aggregating data at the week-level, and these showed no statistically significant autocorrelation overall or at the individual source level for the 2015 data. Furthermore, we also checked that if we grouped at the day-level that there still remains significant autocorrelation; this was indeed the case for the ED, PACU, and ICU, supporting the choice of grouping at the week-level.

Changes in daily measures: admissions, occupancy, and bed-idle time

To assess changes in daily measures, such as admissions, floor occupancy, and bed-idle time, we apply the widely-used quasi-experimental method of interrupted time series (ITS) [22, 24]. Given the relatively short time frame in which implementation is measured, we used an intercept-only approach with an underlying ARIMA model [17]. To account for additional covariates [25], we include controls for the specific day of week and whether the day is a holiday. We conduct our analysis with a day as the unit of measurement and include all data during the interim period (between pre- and post-implementation, with an additional indicator variable for the interim period). ARIMA parameter selection is performed using the corrected Akaike Information Criterion as implemented in the `auto.arima` function [18] in `R` (consistent with best practice per package documentation, we override the two default parameters of using stepwise estimation and model approximations).

The three primary quantities we estimate using ITS are as follows:

- Daily admissions to the four floors of interest (overall and by source). Even though the source of "Floor" has small (typically zero or one) daily admission counts, we elected to use ARIMA as well (instead of a more precise count-based model) for consistency with the approach for the other sources. We also computed this for non-holiday weekdays specifically; to achieve this, we modified the post-implementation indicator variable into two—one for non-holiday weekdays in the post period and another for holidays or weekends in the post period.

- Operational occupancy on the four floors of interest.

- Bed-idle time. This is the sum of the total hours that beds were idle (cleaned and ready but assigned to a patient who is not medically ready). We also assessed the total number of such assignments per day.

For all analyses, confidence intervals (CIs) are reported with 99% coverage given that we are considering multiple outcome measures, many at the subgroup (source) level. All ARIMA model specifications can be found in the Supplementary Material.

Table 3: Implementation results for patients' waits for beds (in hours)

Measure	Source	Measure value *(in hours)* Pre	Post	Change, Pre vs. Post Δ_A *(hours)*	Δ_R *(%)*
Average	PACU	2.36	1.48	$\mathbf{-0.88}$ [−1.52, −0.28]	$\mathbf{-37.4}$ [−55.8, −12.6]
	ED	3.66	2.45	$\mathbf{-1.21}$ [−2.34, −0.16]	$\mathbf{-32.9}$ [−53.7, −3.0]
	Admissions	9.21	6.34	−2.87 [−6.32, 0.90]	−31.2 [−60.4, 15.3]
	ICU	29.10	26.22	−2.88 [−14.34, 8.77]	−9.9 [−42.5, 32.7]
	Floor	4.72	0.95	$\mathbf{-3.77}$ [−6.98, −1.97]	$\mathbf{-79.9}$ [−97.7, −53.4]
	Overall	4.33	3.25	$\mathbf{-1.08}$ [−1.94, −0.15]	$\mathbf{-25.0}$ [−40.9, −3.7]
$Q_{0.5}$	PACU	0.00	0.00	0.00	-
	ED	1.73	0.68	$\mathbf{-1.05}$ [−1.66, −0.59]	$\mathbf{-60.9}$ [−73.7, −43.4]
	Admissions	2.63	1.43	$\mathbf{-1.20}$ [−2.17, −0.43]	$\mathbf{-45.6}$ [−68.9, −17.3]
	ICU	24.36	11.43	−12.93 [−19.73, 5.84]	−53.1 [−70.9, 38.8]
	Floor	2.95	0.20	$\mathbf{-2.75}$ [−4.90, −1.02]	$\mathbf{-93.2}$ [−98.1, −19.7]
	Overall	0.78	0.20	$\mathbf{-0.58}$ [−0.87, −0.38]	$\mathbf{-74.5}$ [−83.9, −59.6]
$Q_{0.75}$	PACU	2.12	0.94	$\mathbf{-1.17}$ [−1.77, −0.57]	$\mathbf{-55.5}$ [−74.8, −32.3]
	ED	4.65	2.39	$\mathbf{-2.26}$ [−4.40, −0.55]	$\mathbf{-48.6}$ [−66.0, −12.3]
	Admissions	7.26	4.33	−2.93 [−10.09, 1.01]	−40.4 [−72.6, 16.6]
	ICU	35.40	31.52	−3.88 [−22.90, 16.67]	−11.0 [−44.1, 53.0]
	Floor	5.82	1.70	$\mathbf{-4.12}$ [−6.76, −0.20]	$\mathbf{-70.8}$ [−97.7, −5.7]
	Overall	3.29	1.87	$\mathbf{-1.42}$ [−2.25, −0.88]	$\mathbf{-43.2}$ [−56.0, −28.1]

Notes. Changes are relative to the "Pre" period. Absolute changes and relative (percentage) changes are denoted Δ_A and Δ_R, respectively. Bootstrapped CIs are shown; changes for which zero is not in the CI are bolded.

3.2 Implementation Results

The total number of patients during the pre- and post-implementation periods is reflected in Table 1. (Note that the post-implementation period contained no holidays, so a version excluding holiday from the pre-implementation period is contained in the Supplementary Material.) Consistent with the implementation of the SSE$^<$ policy, PACU-to-floor transfers decreased for SSE patients specifically following implementation, while ED-to-floor transfers increased given the capacity freed up by such a decrease. Overall, the average total weekday transfers to the floor was comparable. The operational bed occupancy decreased slightly, from 92.0% to 90.0% (change of -2.0%, CI $[-5.2\%, 2.0\%]$).

Patient wait times

Absolute and relative changes in the average, median, and 75th percentile of patient wait times from the pre- and post-implementation periods are shown in Table 3. For the four inpatient floors on which JIT was implemented, average patient wait times decreased overall and across all sources, with statistically significant reductions observed for the PACU, ED, and floor in particular, in addition to overall. When compared with the simulation results, the average reductions are generally comparable with those estimated for most areas with the exception of the ED which experienced a relative change of -32.9% (CI $[-53.7, -3.0]$) as compared with the simulated change of -6.8%. This change also coincided with an increase in the percent of patients with a source of ED (from 24.8% to 27.4%, *cf.* Table 1).

It is worth noting that the median, a more reliable indicator of central tendency for wait times given the heavily right-skewed nature, is reduced significantly overall (with a change of -74.5%, CI $[-83.9, -59.6]$). In contrast, at higher quantiles the relative changes are smaller in magnitude.

Bed-idle time

Weekday bed-idle time was 38.76 hours per day and 18.95 hours per day in the pre- and post-implementation periods, respectively, reflecting a change of -19.81 hours per day (CI $[-27.24, -13.64]$). This corresponds to a 50% reduction in bed-idle time, a substantial improvement in the amount of time that beds spend clean and ready to be occupied but with an assignment to a patient who is not medically ready to transfer to that bed.

The reduction in total idle time is also reflected on a per-assignment basis. In particular, for all assignments which resulted in an idle bed (i.e., the bed was cleaned and assigned to a patient *before* they were medically ready), the average time idle decreased from 3.29 hours per assignment to 1.38 hours (change of -1.91, CI $[-2.14, -1.71]$). (While the time-per-bed decreased, note that the average weekday number of such idle-bed assignments increased slightly, from 11.91 per day to 13.75 per day, a change of 1.84, $[0.12, 3.25]$.)

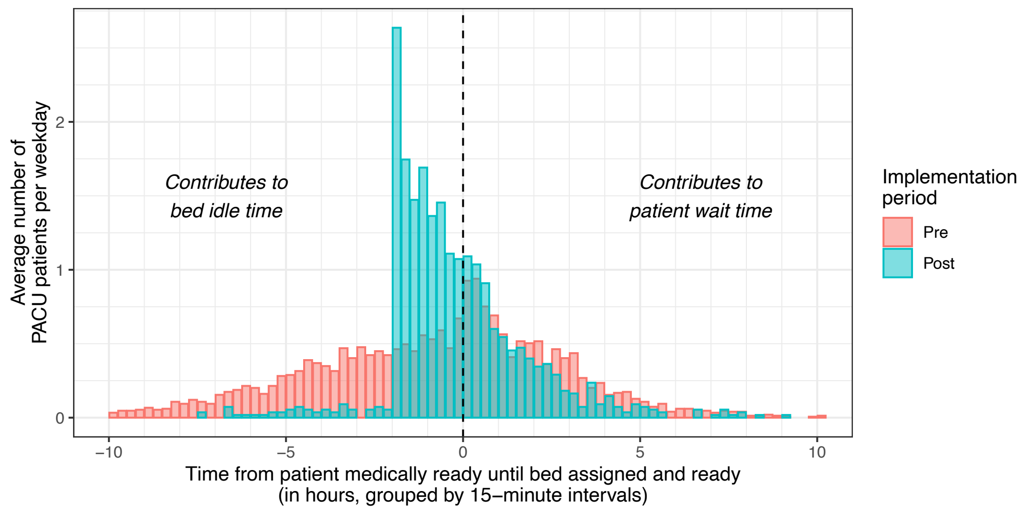
We observed that the reduction in bed-idle time was not nearly as large as projected with the simulation. We believe this is due to how JIT was implemented for patients coming from the PACU. In the simulation we used medical readiness as the trigger to start the bed-assignment process, with an additional administrative delay for the search process; however, given that the medical readiness timestamp is not always reliably available in real time, after discussions with the admitting team, it was decided that bed managers would start looking for beds as soon as patients arrived to the PACU after their surgery (but before they were medically ready to transfer).

Indeed, a closer assessment of the assignment times for weekday PACU patients post-implementation reflects this behavior—the median time from a patient arriving in the PACU to having an assigned and ready bed is 1.17 hours (interquartile range [0.25,2.63]), whereas medical readiness is expected at around two hours. In this period, 45.9% of patients have a recorded medical readiness timestamp within two hours of PACU arrival; among such patients, the median time until medically ready is 1.48 hours, IQR [1.15,1.73]. Even for the majority (62.1%) of such patients, beds are still being assigned prior to being medically ready (*cf.* median time from medically ready to bed ready of -0.53 hours, IQR [-1.18,0.60]). This suggests that there remains significant room for further improvement in bed-idle time by shifting the beginning of the bed search process to actual medical readiness for PACU patients (an improvement which could be enabled by more reliable documentation). While the implemented practice is still significantly better than assigning the beds at the beginning of the day, it is important to acknowledge that it is not medical readiness as we had initially envisioned.

Beds idle versus patients waiting. As noted earlier, bed-idle time is best contextualized as it relates to overall patient wait times. This tradeoff between patient waiting and bed-idle time is illustrated graphically in Figure 2 for the pre- and post-implementation periods for weekday PACU patients, the primary source of bed-idle time. In the post-implementation period, there is better alignment between patient and bed readiness (i.e., proximity to the line at zero hours, where patient medically ready and bed ready coincide). Note that the large increase in the post-implementation period at -2 hours corresponds to patients being assigned beds around the time of arrival to the PACU from surgery (as noted above, the majority of patients do not have medical readiness documented within two hours of PACU arrival and, as such, have medical readiness treated as two hours post-arrival).

From Figure 2, we also see that there are PACU patients who have a ready bed assigned over two hours prior to being medically ready to leave the PACU during the intervention period (i.e., to the left of the -2 hours mark). Overall, 83 patients (6.7% of weekday PACU patients) in the intervention period had a bed assigned *prior* to the patient's arrival to the PACU post-surgery. For the majority of such patients (53), they arrived to the operating room via the ED (in contrast to patients arriving in a scheduled manner from home or from an inpatient floor) and their inpatient bed request was created while in the ED (of these, 50 had their bed assigned while still in the ED, prior to surgery). This group of patients represents further room for improvement in the process by ensuring that patients who are going directly to the operating room from the ED (anticipating a bed need post-surgery) do not have a bed request placed while in the ED (instead following the JIT process for PACU patients). The remaining 30 PACU patients in the intervention period (2.4% of all weekday PACU patients) had a bed assignment that did not directly adhere to the JIT principle, possibly due to patient characteristics that necessitated specific bed placements.

Figure 2: Representation of time from patient medically ready until bed assigned and ready for PACU patients with requests on non-holiday weekdays. Whenever a patient is ready before their bed, patient wait time is incurred (right side of dashed vertical line at 0 hours), while bed idle time is incurred when a patient is not medically ready until *after* their bed is ready (left side). Differences outside of 10 hours are not shown.



Effects for SSE patients

Given the reduction in SSE patients, we also examined changes in wait times specifically for this subgroup of patients. While the average and 75th percentile of wait times decreased for PACU patients *overall*, this behavior masks increased wait times for SSE patients specifically. In particular, SSE PACU patients' average wait times increased by 87.1% (CI $[23.5, 184.1]$, from 2.83 hours to 5.29 hours); in contrast, non-SSE PACU patients' average wait times changed by -51.0% (CI $[-71.9, -25.0]$, from 2.28 hours to 1.11 hours).

This increase in average wait times for SSE patients is driven in part by an increase, among SSE patients who go to the floor, in the percent who stay overnight in the PACU (following their surgery) prior to going to the floor; this percent increased from 8.0% to 18.7% of such patients from the pre- to post-implementation periods (a percentage-point change of 10.7%, CI $[4.4, 17.7]$). Because medical readiness for PACU patients to go to the floor is not always recorded (as noted earlier in the discussion of the simulation model), some of this increase in overnight PACU stays, and hence appearance of an increase in wait times, is likely attributable to an intentional decision to keep such patients overnight in the PACU (before going to the floor) for additional monitoring.

4 Discussion

In this study, we describe the design and implementation of a Just-In-Time (JIT) bed-assignment strategy aimed at increasing the timeliness with which adult surgical patients reach general care floor beds. The implementation of this strategy coincided with the evaluation of another patient flow initiative, which reduced the demand for surgical inpatient beds among short-stay elective patients (SSE). We built a detailed discrete-event simulation to asses the impact of both strategies separately and combined. While it was the joint implementation of these strategies what yielded the largest benefit, the simulation showed that the relative benefit of JIT+Pooling was larger. Implementation-wise, JIT was also the strategy that required greater buy-in from stakeholders and attention to detail in its operationalization. Specifically, it involved two major interventions: i) only medically ready-to-transfer patients would be assigned to empty beds, and ii) pooling four general care floors into groups that would be considered clinically indistinguishable in terms of bed assignment.

As shown in Section 3.2, the combination of these strategies yielded significant benefits that helped ease the congestion the hospital was facing. In the months post-implementation, patient wait times saw significant reductions from two critical upstream areas: the PACU (37.4% reduction on average–from 2.36 to 1.48 hours) and the ED (32.9% reduction on average–from 3.66 to 2.45 hours), which combined account for 85% of all patients. In the specific case of patients transferring from the ED to general care floors, we note that they particularly benefited by the combination of the SSE-reduction strategy and the JIT policy: the former freed up beds in the floors and the latter guaranteed that those beds would not be pre-assigned to patients who would come out of surgery later in the day.

The implementation results differed from those predicted by the simulation model: for most sources, wait times decreased by a larger percentage than predicted. One potential explanation is that there was an increase in the percent of ED admissions to these floors which was not directly captured or modeled in the simulation. One additional challenge is creating precise rules which govern the pooling in the simulation model, as these rules are often implicit and evolve over time along with patients' care needs. Another challenge in evaluating the results is the inherent variability of wait times.

4.1 Implementation and Managerial Insights

The implementation of this strategy required substantial cultural changes. The most significant was transitioning from a decentralized, floor-managed system to a centralized bed-assignment process. The early bed assignments had allowed staff to assign patients to specific team members who would know what to expect throughout their day. In contrast, a JIT policy meant assignments would be done solely by bed managers throughout the day *and* elective surgical patients would no longer have a "guaranteed" pre-assigned bed at the beginning of the day, which created a sense of uncertainty. Notably, the detailed simulation model analysis was essential to assuage stakeholders' concerns.

Additionally, JIT required greater transparency from ED and ICU clinical teams. Before JIT, the process of bed assignment was so uncertain that bed requests were sometimes placed even if the care path for a patient was not fully determined or if the patient was not medically ready to move. In the new process, ED providers are now asked to wait to enter bed requests until their surgical plan is clear: they should place a bed request only if they need to go to the floor before undergoing surgery; otherwise, the bed request should be placed after surgery, from the PACU. If a bed has been assigned to a patient, but no transfer has occurred for two or more hours, the floor's resource nurse is now instructed to call the ED's resource nurse for an update. In the ICU, if a bed request is placed, teams should be ready to do the hand-off within one hour after the bed becomes available.

Finally, bed managers had to adjust their workflows as well. As they took charge of assigning patients to beds directly, they now had to monitor and plan for many more bed assignments throughout the day, especially into the early afternoon.

Further expansion. In this paper, we focus on four surgical units as that was the scope of our simulation model and what allowed us to make the cleanest comparisons of the different strategies. Notably, however, JIT was later implemented across twelve out of the thirteen adult surgical floors at MGH in two additional waves: on May 15, 2017 it was introduced in four more floors and on June 5, 2017 it was implemented on another round of four floors, spanning a total of 314 beds. As soon as it was determined that there were no major unintended consequences from the initial rollout, leadership decided to expand its use without further numerical validation given concerns about upstream (ED and PACU) congestion. To identify and address concerns throughout this process, the main stakeholders held a daily huddle for two weeks after JIT was implemented in the first four units, and for a week after the second and third implementation waves. These 15-minute meetings provided opportunity for all areas to debrief on how the implementation process evolved and how it could be tweaked to address any issues. Strong leadership to guide these discussions before and during the implementation was paramount to success.

Comparison with other wait time reduction strategies. One of the advantages of the JIT+Pooling strategy implemented in this work is that it is relatively resource-neutral by modifying the workflows of existing staff without requiring the creation of new physical capacity or hiring additional staff. In contrast, some other well-known approaches to reduce patient wait times and increase access to inpatient beds can involve significant financial investment. Examples of such strategies include the creation of additional physical bed capacity [14, 1] and the development of additional staff roles to facility inter- and intra-hospital patient movement (e.g., in command centers [19]). However, it is important to note that we did not conduct a financial analysis of our approach (as our primary focus was reducing wait times given the known quality-of-care implications), and the implementation process required a significant investment of time from a large number of staff.

4.2 Limitations and Future Work

JIT can work well when there are no additional constraints for bed assignments other than floor specification; however, there can be challenges when other patient prioritization schemes are in use. For example, in the MGH Department of Medicine, patients are categorized into two acuity levels: "high-acuity" patients are more acute and can only be taken care of by certain teams within certain hospital floors; "low-acuity" patients can be assigned to any floor and any medical team. Moreover, there are more low-acuity patients than high-acuity patients. A JIT policy would have to be modified to incorporate this prioritization so that low-acuity patients do not fully occupy all the beds that high-acuity patients need while also balancing their respective wait times.

Finally, JIT's effectiveness in addressing intra-day congestion is restricted to the configuration of beds and their assigned clinical services within which it operates. The bed-assignment process can be further optimized when the allocation of clinical services to beds guarantees that, on average, there are enough available beds to meet demand for all the different services.

5 Conclusions

A system-wide analysis of the surgical bed-assignment process allowed us to design and implement a Just-In-Time policy which, by changing the process for a relatively narrow population (scheduled surgical patients) and combining it with a focused, separate pathway for a significant percentage of short-stay scheduled surgical patients, translated into significant reductions in wait times for PACU and ED patients. Qualitatively, this has increased staff awareness around throughput and the strategic management of limited resources. The contributions of this work are two-fold: i) the design and numerical validation of major changes in patient-flow processes at a major academic medical center and ii) the managerial insights that led to a successful implementation. Although this is a single-site study, we believe our approach is sufficiently general to be applicable to any hospital facing similar challenges with their surgical patient population.

Declarations

Competing interests. The authors do not declare any competing interests related to this work.

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Supplementary Material

This Supplementary Material includes additional details that augment the main text. Specifically, we include the following:

1. details of the simulation model and assumptions;
2. technical details on simulation validation and experiments;
3. details on the SSE reduction scenarios and a sensitivity analysis of these scenarios based on the extent of the reduction of patient demand per the SSE policy;
4. simulation results for bed-idle time and occupancy (Table SM3);
5. ARIMA model parameters for the interrupted time series models; and
6. implementation results (analogous to Table 3) with holiday weeks removed.

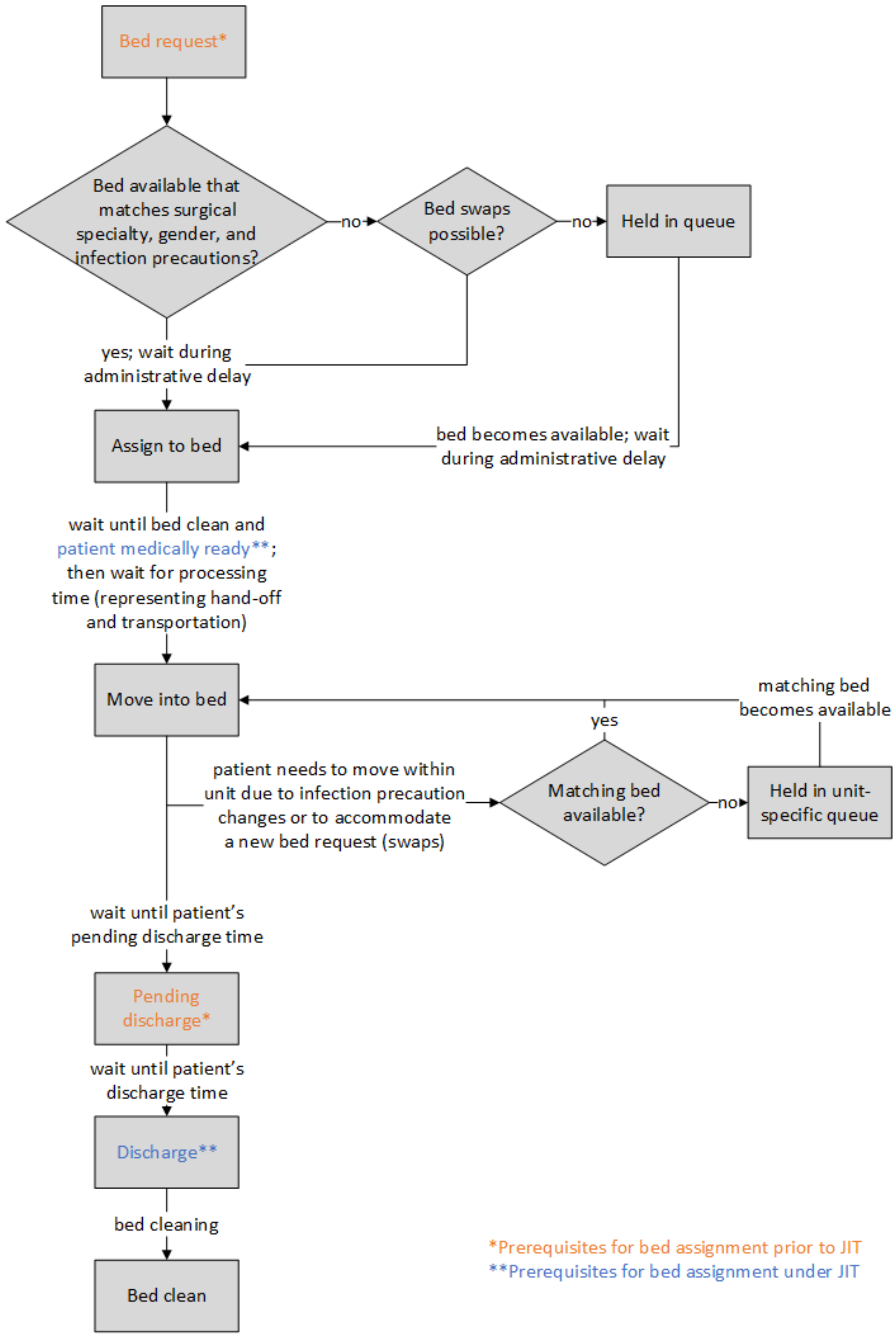
SM1 Simulation model and assumptions

As described in Section 2 in the main text, the simulation input included timestamps of all patient movements within the different areas of the hospital: the perioperative environment, the emergency department, and in the inpatient floors, and the corresponding bed requests. We take timestamps such as when patients were ready to transfer out and their discharge times as fixed; we consider these as part of clinical processes whose modeling is not related to the bed-assignment process.

The patient flow model (Figure SM1) starts with the arrival of each patient at his historical bed request time. Because the precise historical rules for prioritization are not standardized or documented, in the base scenario the model prioritizes patients for assignment based on the order that they were historically assigned. Once a patient is next to be assigned, the simulation looks for a bed available for assignment that matches his needs in terms of surgical specialty, gender, and infection precautions. The simulation includes an administrative delay, sampled from historical data, to account for the fact that while assignments are made instantaneously when they become feasible in the simulation, in the real world it is a manual process that is not instantaneous.

Once a patient is assigned to a bed, he must wait until becoming medically ready to continue the process. Most patients in the simulation become medically ready at the time of their bed request, but elective surgical patients may need to wait at this point. Once the patient is medically ready he starts waiting for his bed to become available to occupy. This means that the patient or closure that was occupying the bed previously must leave and the bed must be cleaned. This wait can range from zero, when the patient was assigned to a bed that was already ready, to over twelve hours, in the case where a pending discharge was entered far in advance of the actual discharge. Cleaning times are sampled from the historical data. Once the bed becomes available the patient-wait-for-bed time ends. On the other hand, if the patient was assigned to a bed that was ready before the patient's medical readiness, the simulation registers bed-idle time for the bed from the moment it was ready until the moment the patient is medically ready. When both patient and bed are ready, the patient waits for a transfer processing time, also drawn from the historical data, before he occupies his bed.

Figure SM1: A visual representation of the logic underlying the patient flow simulation model



The patient then stays in his bed until his historical pending discharge time (unless he is subject to infection precautions changes or bed swaps, which are described later). In the base scenario, at the time of the historical pending discharge, the patient's bed becomes available for assignment. Before the bed becomes available for assignment to patients, the simulation first checks whether there is a closure for staffing or maintenance that needs to be implemented on that unit. If there is such a waiting closure, the bed will be closed for the historical duration of the closure.

The patient then waits until his historical departure time from the unit before relinquishing his actual bed for cleaning. The model uses historical departure times based on the belief that small changes in patients' intraday wait times would not affect their eventual discharge times.

The simulation model closely resembles reality by including bed closures, changes in patients' infection precautions, and bed swaps (i.e., moving a patient to another bed in the same floor). In the four floors of interest, 116 out of 129 beds (90%) are semiprivate and there were a total of 69,586 bed-closure hours in 2015, effectively reducing the floors' operational capacity to 121 beds.

Two types of bed closures occur in the simulation. First, historical closures due to maintenance or staffing shortages are replicated in the model. At the historical time of a closure start, the simulation will look for a bed to close on the appropriate unit. If no bed is available at that time, the next bed to become available will be closed. The closure will last for the historical duration of the closure. Second, patients with an infection precaution close the neighboring bed when being in a semiprivate room alone. In the case of MRSA (methicillin-resistant *Staphylococcus aureus*), VRE (vancomycin-resistant *Enterococcus*), or both MRSA and VRE, the bed can be opened by finding an appropriate patient to cohort. As in practice, the model executes bed swaps to improve cohorting. Changes in patients' infection precautions are replicated at their historical times, potentially necessitating bed swaps. Since private rooms are so highly demanded, we assume that patients only stayed in them historically when absolutely required. In the simulation input, such patients were assigned the infection precaution "non-cohortable." The model assumes that only non-cohortable patients can be assigned to private rooms.

Bed swaps are incorporated in the simulation using the following procedure. When a semi-private bed becomes available for assignment (either because of a closure ending or a pending discharge) and there is no waiting patient that is appropriate for the bed, the simulation checks whether there is a patient on the unit that is currently in a room alone and matches the characteristics of the bed that is now available for assignment. If such a patient exists, he will be swapped into the bed that the first patient is leaving and his bed will be made available to waiting patients instead of the original bed. This allows more flexibility in the patients that can be accommodated since the bed that becomes available to waiting patients is now suitable for any patient. Bed swaps can also be initiated when a patient's infection precautions change. Upon a change in a patient's infection precautions, the following procedures are followed.

If the patient is in a semi-private room with a roommate (who will no longer match infection precautions):

i) Check to see if there is a room on the unit that is available for the patient or his roommate to move into with another patient that they now match. If so, execute this move.

ii) If there is no room with a matching patient, see if there is an empty room available to move the patient or roommate to. If so, execute this move.

iii) If this does not work, leave the patient together with his roommate until another bed on the unit becomes available. Any time a bed becomes available, check to see if either the patient or his roommate can be moved into it.

If the patient is in a semi-private room with no roommate:

i) Check to see if there is now an opportunity to cohort this patient with another patient that matches his new infection precautions. If the new infection precaution is non-cohortable, look for a private room for this patient.

ii) If a cohorting situation or private room is not found, leave the patient in the semi-private room.

Finally, if the patient is in a private room and is no longer non-cohortable:

i) Check to see if the patient can now be cohorted with another patient on the unit.

ii) If not, look for an empty semi-private room for this patient.

iii) If neither i) nor ii) are successful, leave the patient in the private room for the time being.

SM2 Simulation validation and experiments

To validate our simulation model, we first ran a base scenario and statistically compared its performance to historical performance. In the base scenario, patients needed to be assigned to a bed on the same floor that they were historically assigned. Since the historical rules for prioritization were not standardized or documented, the model prioritized patients for assignment based on the order that they were historically assigned. All patients could be assigned to "pending discharge" beds (beds in which the current patient is indicated as leaving at some time later that day), and bed assignments for elective surgical patients could begin as soon as their bed requests had been generated (i.e., before their surgeries).

We compared the distribution of patients' wait times between the 2015 historical data and the output of the simulation's base scenario. Following the approach of Montgomery and Runger [28], we calculated the 95% confidence interval (CI) on the difference in means (with validation occurring whenever the interval contains zero). For the whole patient population, the average patient wait time was 4.76 and 4.88 hours for historical and simulation, respectively, with confidence interval for the difference of $[-0.38, 0.13]$. As 0 is contained in this confidence interval, we concluded that there were no statistically significant differences in the average wait time between historical and the simulation. Likewise, we compared the simulation model for each subset of the population when partitioned by source, by patient infection precautions, by weekday of the bed request, or by specific floor destination (see Table SM1). While the CI for patients from the ED ($[-0.35, -0.01]$) does not contain 0, it is not adjusted for multiple testing and as such is not a concern for model validation (indeed, standard multiple testing corrections, e.g., Holm, yield a non-significant result; in other words, per this approach, the model is validated in this subset).

For the results throughout the text, we present the average across 100 simulation runs. We chose 100 because with this choice of number of simulation runs, the base scenario yielded estimates that were within a practical tolerance for relevant stakeholders at the hospital. In particular, for the average and quantiles of interest, the overall wait time had a standard error below 0.005. Not surprisingly, the standard errors were higher for the sources with fewer observations, but all were still within a practically reasonable tolerance in this setting.

SM3 SSE reduction scenarios and sensitivity analysis

Before the actual SSE bed strategy was implemented, it was not known how this would change demand for floor beds for these patients. Therefore, we considered a spectrum of possible scenarios. Among the 898 SSE patients in 2015 who went to the four surgical floors of interest, 653 (72.7%) had a total hospital length of stay (LOS) of zero or one days, with the remaining 245 (27.3%) having a LOS of ≥ 2 days. The SSE reduction policy was not designed to affect the floor placement of such longer-LOS SSE patients; therefore, in the simulation we do not consider reductions in this group (in the actual implementation, this average daily number of SSE patients with $\geq$ 2-day LOS decreased slightly, although the change was not statistically significant).

Instead, we consider percent reductions in the zero- or one-day LOS patients (which we call "eligible SSE patients"). In particular, we consider, for $P \in \{0, 1, 2, \ldots, 100\}$, what the change in patient wait times is if P% of eligible SSE patients require a floor bed. The scenario $P = 100$ corresponds to the base scenario (where all of the 653 eligible SSE patients still require a bed) and $P = 0$ corresponds to *none* of the eligible SSE patients going to the floor.

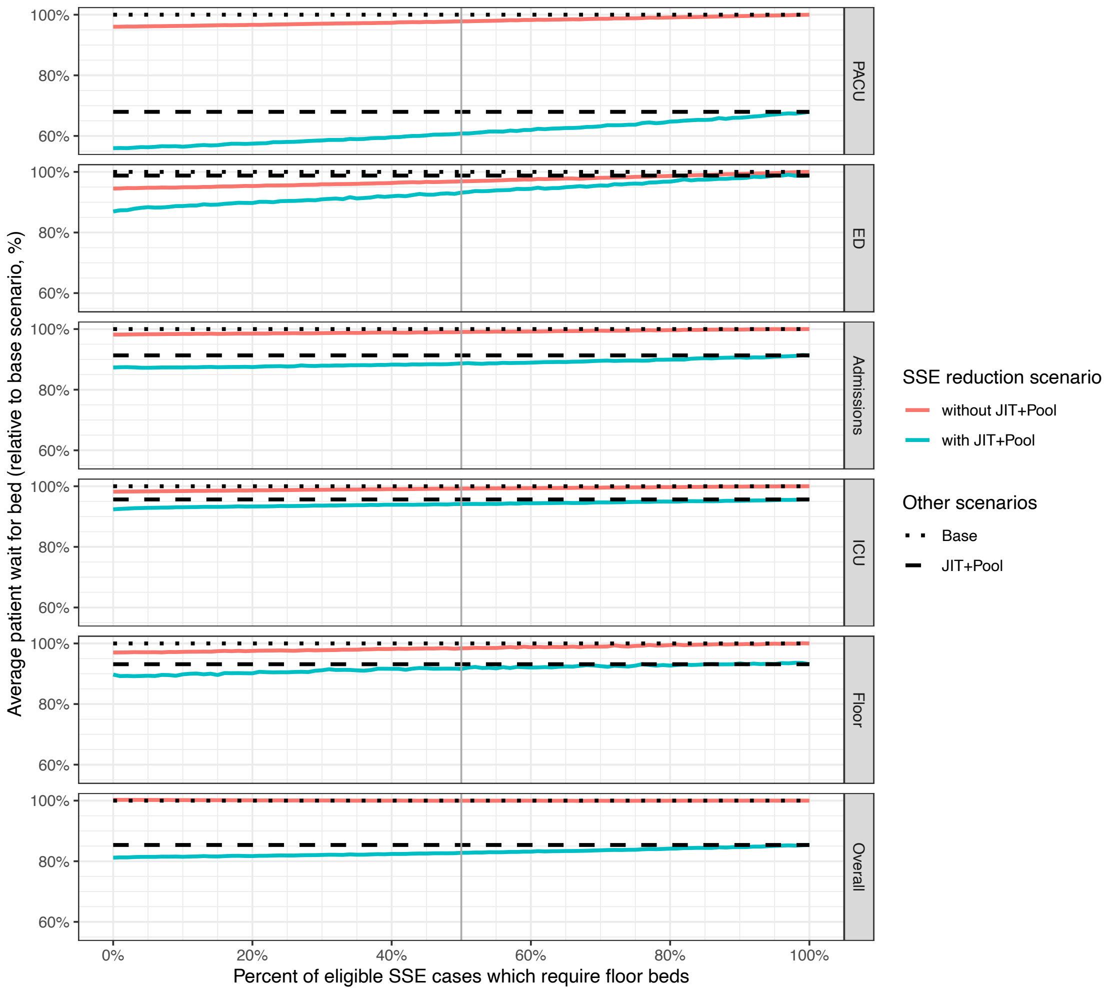
In the main text, we single out one scenario that we denoted $\text{SSE}^{<}$. This corresponds to the case where $P = 50$, i.e., the eligible SSE patients going to the floor are at 50% of their historical volume. We chose this scenario to present because it corresponds closely with the actual reduction observed during the implementation, where the average daily eligible SSE patient volume decreased to 42.7% of its pre-implementation value (CI $[25.8\%, 65.0\%]$).

In Table SM2, we also add the scenario SSE^{0} for comparison; this corresponds with the extreme case where $P = 0$. In Figure SM2, we show the corresponding results for the various eligible SSE patient reduction scenarios (results for the median are qualitatively consistent with these and Table 2 and, as such, are not shown here).

SM4 ARIMA model specifications

In this section, we include the chosen ARIMA model parameters per the selection process detailed in the main text. The final reported models in the main text do not include seasonality, though we performed a comparison with weekly (7-day) seasonality included (a comparison for daily admissions, as per Table 1, is included below); model estimates for changes post-implementation were generally comparable so we elected to include the simpler approach.

Figure SM2: SSE reduction sensitivity analysis for relative changes in average patient wait times



Notes. Comparison scenarios are detailed in Table 2 in the main text. All results are averaged over 100 simulations. The vertical line at 50% corresponds to the scenario SSE$^{<}$.

We use ARIMA$(p, d, q)(P, D, Q)$ to denote a model with p autoregressive terms, d differencing terms, q moving average terms, P seasonal autoregressive terms, D seasonal differencing terms, and Q seasonal moving average terms (measurements are at the daily level). Model parameters, coefficients, and summary statistics (namely, corrected Akaike Information Criterion [AICc] and in-sample root mean squared error [RMSE]) are shown as follows: daily admissions in Tables SM4 and SM5 for overall and weekdays, respectively; and occupancy and bed-idle time (both overall and assignment volume per day) in Table SM6.

Finally, we performed a comparison for daily admissions of the non-seasonal model with a version with weekly seasonality. While the automated selection process does identify non-zero seasonal parameters in some cases (i.e., $P + D + Q > 0$), the estimates for the post-implementation coefficient specifically are similar. This is demonstrated in Table SM7 where the corresponding estimated confidence intervals are shown (*cf.* Table 1). In all cases, the (p, d, q) parameters were the same. For this reason, we elected to use the simpler models without seasonality.

SM5 Implementation results with holidays excluded

The post-implementation period included no hospital-wide holidays (overall, there are nine institutional holidays per year, resulting in nine holiday weeks). While holidays themselves typically have reduced demand for hospital beds (due to changes in emergency department visit volume and scheduled surgical volume), surrounding days within holiday *weeks* also tend to have reduced demand as well. Therefore, the results shown in Table 3 in the main text potentially underestimate the effect of implementation (as the pre-implementation period includes 7 holiday weeks out of a total of 30 complete weeks, compared to 0 out of 11 post-implementation).

To augment those results, we also conducted the comparison where holiday weeks are excluded from the pre-implementation period. The corresponding results, analogous to Table 3, are shown in Table SM8. Overall, the estimates for changes tended to decrease (i.e., larger reductions in wait times).

Table SM1: Validation results: Patients' wait times for multiple partitions, with historical in gray, simulation in white, and n the number of bed requests in each subset. Note that confidence intervals (CIs) are at the 95% level and are not adjusted for multiple testing.

Partition	n	CI Δ means	Mean	St.dev.	$Q_{0.05}$	$Q_{0.25}$	$Q_{0.5}$	$Q_{0.75}$	$Q_{0.95}$
Overall	10,771	[-0.38, 0.13]	4.76	13.29	0.00	0.00	0.53	3.73	24.61
			4.88	13.30	0.00	0.00	0.62	4.03	25.22
By source									
PACU	6,204	[-0.24, 0.04]	2.45	5.52	0.00	0.00	0.00	2.12	18.63
			2.55	5.73	0.00	0.00	0.00	2.28	19.02
ED	2,824	[-0.35, -0.01]	2.78	4.59	0.03	0.13	0.70	3.01	13.83
			2.96	4.77	0.05	0.18	0.87	3.32	14.80
Admissions	862	[-2.38, 1.65]	11.66	29.42	0.03	0.62	3.15	17.17	41.44
			12.02	29.38	0.10	1.22	3.79	16.98	41.62
ICU	701	[-1.79, 2.08]	24.05	25.44	1.28	5.47	12.05	32.93	76.70
			23.91	25.14	0.97	5.88	12.40	33.68	76.30
Floor	180	[-3.70, 3.74]	7.31	24.71	0.02	0.22	2.49	5.52	22.83
			7.29	24.59	0.02	0.45	2.25	4.99	23.90
By patient infection precautions									
None	9,921	[-0.34, 0.04]	4.04	9.56	0.00	0.00	0.43	3.25	22.55
			4.19	9.61	0.00	0.00	0.52	3.65	22.98
Influenza	10	[-3.04, 1.58]	2.24	3.07	0.00	0.10	0.60	4.26	7.24
			2.97	2.85	0.17	0.17	2.72	5.58	6.45
MRSA	107	[-2.71, 3.02]	7.35	14.61	0.00	0.03	1.52	7.33	31.23
			7.20	14.53	0.00	0.03	1.27	6.08	33.70
VRE	164	[-2.25, 2.96]	9.31	16.48	0.00	0.20	1.87	8.98	38.97
			8.96	16.45	0.00	0.15	1.03	9.29	38.92
MRSA & VRE	15	[-20.14, 21.54]	29.04	37.10	0.13	1.52	19.80	45.63	105.71
			28.34	35.25	0.03	0.68	18.97	47.23	111.80
Non-cohortable	554	[-2.92, 3.70]	15.29	38.74	0.00	0.29	4.83	18.59	57.75
			14.90	38.40	0.00	0.35	4.05	18.35	55.92
By weekday of the bed request									
Sunday	689	[-0.77, 1.15]	4.97	12.54	0.00	0.10	0.55	3.20	30.81
			4.78	12.27	0.00	0.12	0.62	2.85	32.82
Monday	2,028	[-1.01, 0.74]	3.80	19.59	0.00	0.00	0.03	1.62	20.30
			3.94	19.77	0.00	0.00	0.00	1.82	20.90
Tuesday	2,013	[-0.77, 0.35]	5.73	12.50	0.00	0.00	1.03	4.68	26.96
			5.94	12.57	0.00	0.00	1.08	5.25	28.13
Wednesday	1,788	[-0.71, 0.19]	5.17	9.48	0.00	0.00	1.37	5.09	23.92
			5.43	9.53	0.00	0.00	1.52	5.65	25.52
Thursday	1,555	[-0.71, 0.31]	4.04	10.03	0.00	0.00	0.58	3.50	19.39
			4.24	10.02	0.00	0.00	0.78	4.08	19.82
Friday	1,885	[-0.53, 0.53]	4.50	11.52	0.00	0.00	0.32	3.20	25.25
			4.50	11.26	0.00	0.00	0.40	3.72	24.28
Saturday	813	[-0.87, 0.92]	5.67	12.69	0.00	0.12	1.13	4.72	33.41
			5.65	12.70	0.00	0.15	1.07	4.68	32.88
By specific floor destination (# beds)									
Ortho & Uro (36)	3,366	[-0.78, 0.27]	4.05	15.10	0.00	0.00	0.35	3.13	22.51
			4.30	15.24	0.00	0.00	0.48	3.92	23.02
Ortho (30)	2,522	[-0.59, 0.18]	3.58	9.54	0.00	0.00	0.22	2.50	21.65
			3.79	9.64	0.00	0.00	0.32	2.98	22.63
Gen. Surg. (36)	2,735	[-0.39, 0.59]	5.38	12.73	0.00	0.00	0.80	4.33	26.89
			[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]

Table SM2: Additional simulation results for patients' waits for beds (in hours)

Source	Intervention	Average Value	Average Δ_R	$Q_{0.5}$ Value	$Q_{0.5}$ Δ_R	$Q_{0.75}$ Value	$Q_{0.75}$ Δ_R
PACU	Base	2.59		0.00		2.34	
	SSE^0	2.49	−4.0	0.00		1.96	−16.4
	JIT+Pool+SSE^0	1.45	−44.0	0.00		1.00	−57.4
ED	Base	3.57		1.12		4.22	
	SSE^0	3.37	−5.5	0.98	−12.0	3.93	−6.8
	JIT+Pool+SSE^0	3.10	−13.1	0.81	−27.9	2.89	−31.5
Admissions	Base	10.59		3.71		11.28	
	SSE^0	10.40	−1.8	3.64	−1.8	10.71	−5.1
	JIT+Pool+SSE^0	9.25	−12.7	2.26	−39.1	9.70	−14.0
ICU	Base	26.85		21.31		35.45	
	SSE^0	26.37	−1.8	20.06	−5.9	35.24	−0.6
	JIT+Pool+SSE^0	24.80	−7.6	16.92	−20.6	34.09	−3.8
Floor	Base	9.08		2.75		5.77	
	SSE^0	8.80	−3.0	2.60	−5.4	5.63	−2.4
	JIT+Pool+SSE^0	8.14	−10.3	1.40	−49.1	4.38	−24.2
Overall	Base	4.76		0.54		4.05	
	SSE^0	4.78	0.3	0.43	−21.2	3.89	−4.0
	JIT+Pool+SSE^0	3.87	−18.8	0.37	−32.4	2.17	−46.4

Notes. See notes for Table 2 in the main text. The additional scenario added here, SSE^0, corresponds with *no* eligible SSE patients (i.e., SSE patients with length of stay at most one day) going to the inpatient surgical floors.

Table SM3: Simulation results for other metrics—daily averages for bed-idle time and occupancy

Intervention	Bed-idle time *(in hours)* Value (SE)	Bed-idle time Δ_R	Operational occupancy *(%)* Value (SE)	Operational occupancy Δ_A
Base	54.6 (0.008)		88.5 (0.004)	
SSE$^<$	54.5 (0.029)	−0.1	87.5 (0.006)	−1.0
SSE^0	53.9 (0.008)	−1.3	86.6 (0.004)	−1.9
JIT	7.2 (0.003)	−86.8	88.7 (0.004)	0.2
JIT+Pooling	7.7 (0.006)	−85.8	88.6 (0.005)	0.1
JIT+Pooling+SSE$^<$	7.8 (0.007)	−85.7	87.8 (0.006)	−0.7
JIT+Pooling+SSE^0	7.7 (0.005)	−85.8	87.0 (0.005)	−1.6

Notes. We denote standard errors (across 100 simulation runs) as "(SE)"; Δ_A and Δ_R denote absolute and relative (percentage) change as compared with "Base," respectively. Bed-idle time and occupancy are computed on a daily basis with weekends and holidays excluded.

Table SM4: ARIMA model coefficients and summary statistics for changes in **Daily Admissions**.

Source	PACU (all)	PACU (non-SSE)	PACU (SSE)	ED	Admissions	ICU	Floor	*Overall*
Variable	*Coefficient (Standard error)*							
(Intercept)	1.94 (0.66)	1.55 (0.65)	0.38 (0.26)	7.88 (0.42)	1.29 (0.24)	1.79 (0.18)	0.28 (0.11)	13.18 (0.80)
Indicators								
Holiday	−21.67 (1.63)	−19.62 (1.53)	−1.62 (0.63)	−0.66 (1.03)	−2.46 (0.59)	0.94 (0.45)	−0.26 (0.28)	−23.72 (1.95)
Interim	−0.93 (0.80)	0.42 (0.95)	−1.15 (0.34)	0.68 (0.55)	−0.02 (0.32)	−0.03 (0.25)	0.37 (0.15)	0.10 (0.91)
Post	−0.59 (0.53)	0.32 (0.63)	−1.02 (0.23)	1.03 (0.37)	0.03 (0.21)	0.03 (0.17)	−0.21 (0.10)	0.31 (0.60)
Day of week								
Mon	25.04 (0.97)	23.54 (0.88)	1.48 (0.36)	−1.15 (0.59)	1.90 (0.34)	−0.97 (0.25)	−0.01 (0.16)	24.76 (1.22)
Tue	24.38 (0.91)	20.01 (0.86)	4.39 (0.35)	−1.86 (0.58)	1.73 (0.33)	−0.37 (0.26)	−0.07 (0.16)	23.80 (1.10)
Wed	21.13 (0.91)	18.67 (0.85)	2.48 (0.35)	−1.93 (0.58)	1.51 (0.33)	−0.39 (0.25)	0.20 (0.16)	20.51 (1.11)
Thu	14.40 (0.91)	12.18 (0.85)	2.23 (0.35)	−1.51 (0.58)	2.01 (0.33)	−0.22 (0.25)	0.45 (0.16)	15.11 (1.11)
Fri	19.93 (0.91)	16.67 (0.85)	3.31 (0.35)	−0.60 (0.57)	0.69 (0.33)	−0.02 (0.26)	0.04 (0.16)	20.05 (1.09)
Sat	1.33 (0.95)	0.85 (0.87)	0.42 (0.35)	−0.44 (0.58)	−0.12 (0.33)	0.35 (0.24)	0.33 (0.16)	1.41 (1.20)
AR_1	−0.09 (0.06)	1.74 (0.03)				−1.47 (0.04)		−0.16 (0.06)
AR_2		−0.91 (0.04)				−0.94 (0.05)		
MA_1		−1.78 (0.02)				1.52 (0.03)		
MA_2		0.98 (0.02)				0.95 (0.04)		
Measure	*Value*							
ARIMA	(1,0,0)	(2,0,2)	(0,0,0)	(0,0,0)	(0,0,0)	(2,0,2)	(0,0,0)	(1,0,0)
AICc	1855.16	1819.15	1253.43	1562.71	1211.08	1060.00	734.75	1972.32
RMSE	4.34	4.05	1.69	2.75	1.58	1.22	0.74	5.22

Notes. Holiday, Interim, and Post are indicator (0/1) variables; day of week is relative to Sunday; AR_k and MA_k denote autoregressive and moving average terms of order k, respectively; AICc denotes corrected Akaike Information Criterion; and RMSE denotes root mean square error. Seasonal parameters are not estimated ($P = D = Q = 0$) and are therefore omitted. Coefficients not estimated are left blank.

Table SM5: ARIMA model coefficients and summary statistics for changes in **Weekday Daily Admissions**. Notation as in Table SM4.

Source	PACU (all)	PACU (non-SSE)	PACU (SSE)	ED	Admissions	ICU	Floor	*Overall*
Variable	*Coefficient (Standard error)*							
(Intercept)	1.99 (0.69)	1.80 (0.66)		7.90 (0.44)	1.38 (0.25)	1.77 (0.19)	0.32 (0.12)	13.30 (0.84)
Indicators								
Holiday	−21.66 (1.63)	−19.96 (1.55)	−1.64 (0.63)	−0.66 (1.03)	−2.44 (0.59)	0.94 (0.45)	−0.25 (0.28)	−23.71 (1.95)
Interim	−0.93 (0.80)	0.25 (0.83)	−1.11 (0.33)	0.68 (0.55)	−0.02 (0.32)	−0.03 (0.25)	0.37 (0.15)	0.10 (0.91)
Post-weekday	−0.50 (0.64)	0.86 (0.65)	−1.30 (0.26)	1.06 (0.43)	0.19 (0.25)	−0.01 (0.20)	−0.16 (0.12)	0.52 (0.73)
Post-weekend	−0.79 (1.03)	−0.63 (1.02)	−0.21 (0.38)	0.95 (0.68)	−0.37 (0.39)	0.12 (0.31)	−0.35 (0.18)	−0.20 (1.19)
Day of week								
Mon	24.97 (1.02)	23.20 (0.93)	1.92 (0.28)	−1.18 (0.62)	1.77 (0.35)	−0.94 (0.26)	−0.06 (0.17)	24.59 (1.26)
Tue	24.31 (0.96)	19.63 (0.91)	4.84 (0.26)	−1.89 (0.61)	1.60 (0.35)	−0.34 (0.28)	−0.11 (0.16)	23.63 (1.15)
Wed	21.06 (0.96)	18.30 (0.91)	2.93 (0.26)	−1.95 (0.61)	1.37 (0.35)	−0.36 (0.26)	0.15 (0.16)	20.34 (1.16)
Thu	14.33 (0.96)	11.81 (0.91)	2.67 (0.26)	−1.54 (0.61)	1.87 (0.35)	−0.19 (0.26)	0.40 (0.16)	14.93 (1.16)
Fri	19.87 (0.95)	16.27 (0.91)	3.75 (0.26)	−0.63 (0.60)	0.55 (0.35)	0.00 (0.27)	−0.01 (0.16)	19.88 (1.14)
Sat	1.33 (0.95)	0.93 (0.87)	0.59 (0.27)	−0.44 (0.58)	−0.11 (0.33)	0.35 (0.24)	0.33 (0.16)	1.42 (1.19)
AR_1	−0.09 (0.06)					−1.47 (0.04)		−0.16 (0.06)
AR_2						−0.94 (0.05)		
MA_1						1.52 (0.03)		
MA_2						0.95 (0.05)		
Measure	*Value*							
ARIMA	(1,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(2,0,2)	(0,0,0)	(1,0,0)
AICc	1857.28	1823.71	1250.10	1564.86	1211.75	1062.10	736.13	1974.25
RMSE	4.34	4.13	1.68	2.75	1.57	1.22	0.74	5.22

Table SM6: ARIMA model coefficients and summary statistics for changes in **Bed Occupancy and Bed-Idle Time**. Notation as in Table SM4. Occupancy is measured on a scale of 0-100%, and bed-idle time is reported both overall and in number of daily idle-bed assignments.

Outcome	Occupancy (%)	Total daily bed-idle hours	Total daily bed-idle assignments
Variable	*Coefficient (Standard error)*		
(Intercept)	76.13 (0.89)		1.47 (0.62)
Indicators			
Holiday	−13.04 (1.53)	−50.11 (6.29)	−14.58 (1.45)
Interim	0.27 (1.92)	2.17 (3.34)	0.28 (0.78)
Post-weekday	−1.63 (1.41)	−20.44 (2.64)	1.68 (0.61)
Post-weekend	−4.90 (1.58)	3.91 (3.81)	0.25 (0.95)
Day of week			
Mon	13.32 (0.83)	64.20 (2.76)	17.01 (0.87)
Tue	18.87 (0.84)	41.95 (2.61)	11.87 (0.85)
Wed	18.08 (0.88)	29.38 (2.61)	7.96 (0.85)
Thu	14.11 (0.88)	26.29 (2.62)	6.53 (0.85)
Fri	13.16 (0.84)	35.13 (2.58)	9.58 (0.85)
Sat	4.12 (0.75)	2.97 (2.65)	−0.08 (0.80)
AR_1	1.40 (0.16)		
AR_2	−0.62 (0.12)		
MA_1	−0.93 (0.17)		
MA_2	0.41 (0.08)		
Measure	*Value*		
ARIMA parameters	(2,0,2)	(0,0,0)	(0,0,0)
AICc	1906.34	2718.30	1785.83
RMSE	4.59	16.76	3.86

Table SM7: Comparison of confidence interval (CI) estimates for changes in daily admissions for ARIMA models with and without weekly (7-day) seasonality. ARIMA parameters $(p, d, q)(P, D, Q)$ are also shown.

ARIMA type	Without seasonality		With seasonality	
Measure	CI	Parameters	CI	Parameters
Source				
PACU (all)	[−1.96,0.79]	(1,0,0)(0,0,0)	[−1.96,0.79]	(1,0,0)(0,0,0)
PACU (non-SSE)	[−1.31,1.94	(2,0,2)(0,0,0)	[−1.31,1.94]	(2,0,2)(0,0,0)
PACU (SSE)	[−1.60,−0.44]	(0,0,0)(0,0,0)	[−1.60,−0.44]	(0,0,0)(0,0,0)
ED	[0.09,1.98]	(0,0,0)(0,0,0)	[0.17,1.85]	(0,0,0)(0,0,1)
Admissions	[−0.52,0.57]	(0,0,0)(0,0,0)	[−0.52,0.57]	(0,0,0)(0,0,0)
ICU	[−0.40,0.46]	(2,0,2)(0,0,0)	[−0.43,0.50]	(2,0,2)(0,0,1)
Floor	[−0.47,0.04]	(0,0,0)(0,0,0)	[−0.41,−0.03]	(0,0,0)(1,0,1)
Overall	[−1.23,1.86]	(1,0,0)(0,0,0)	[−1.23,1.86]	(1,0,0)(0,0,0)

Table SM8: Implementation results for patients' waits for beds (in hours), **excluding holiday weeks**

Measure	Source	Measure value *(in hours)* Pre	Post	Change, Pre vs. Post Δ_A *(hours)*	Δ_R *(%)*
Average	PACU	2.60	1.48	-1.12 $[-1.79, -0.47]$	-43.2 $[-59.7, -21.2]$
	ED	4.00	2.45	-1.55 $[-2.72, -0.36]$	-38.7 $[-57.4, -8.2]$
	Admissions	9.41	6.34	-3.07 $[-6.57, 0.81]$	-32.6 $[-62.5, 12.0]$
	ICU	31.01	26.22	-4.78 $[-17.62, 6.63]$	-15.4 $[-45.9, 25.2]$
	Floor	4.85	0.95	-3.90 $[-7.42, -1.92]$	-80.4 $[-97.7, -51.9]$
	Overall	4.66	3.25	-1.41 $[-2.26, -0.45]$	-30.2 $[-44.6, -10.3]$
$Q_{0.5}$	PACU	0.10	0.00	-0.10 -	-100.00 -
	ED	1.97	0.68	-1.29 $[-2.11, -0.76]$	-65.7 $[-78.0, -51.1]$
	Admissions	2.75	1.43	-1.32 $[-2.26, -0.52]$	-47.9 $[-70.1, -20.4]$
	ICU	25.79	11.43	-14.36 $[-20.52, 2.22]$	-55.7 $[-71.8, 8.3]$
	Floor	3.08	0.20	-2.88 $[-5.13, -1.12]$	-93.5 $[-98.2, -23.3]$
	Overall	0.93	0.20	-0.73 $[-1.05, -0.49]$	-78.6 $[-86.7, -65.5]$
$Q_{0.75}$	PACU	2.37	0.94	-1.42 $[-2.00, -0.77]$	-60.2 $[-77.1, -38.9]$
	ED	5.08	2.39	-2.69 $[-5.07, -0.78]$	-53.0 $[-69.1, -14.8]$
	Admissions	8.02	4.33	-3.69 $[-13.05, 0.10]$	-46.0 $[-77.4, 0.7]$
	ICU	45.58	31.52	-14.06 $[-32.33, 13.04]$	-30.9 $[-52.5, 36.9]$
	Floor	5.82	1.70	-4.12 $[-7.42, -0.20]$	-70.8 $[-97.6, -1.5]$
	Overall	3.63	1.87	-1.77 $[-2.67, -1.05]$	-48.6 $[-60.9, -32.8]$

Notes. Changes are relative to the "Pre" period. Absolute changes and relative (percentage) changes are denoted Δ_A and Δ_R, respectively. Bootstrapped CIs are shown. All holiday weeks are excluded (7 weeks in pre, 0 weeks in post period).