MLD-603

Operations Management for Improving Public Services

Dr. Soroush Saghafian

PACU Bed-block at Brigham and Women's Hospital

Final Report

March 24th, 2016

Jason Sarfo-Annin, Ned Lederer, Joy Wu, Xuezhi Dong

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Abstract

In recent years, Medicare and private payers shifted a growing number of surgeries with relatively short postoperative recovery time from inpatient to outpatient level reimbursements. As a result, many hospitals, including Brigham and Women's Hospital (BWH), are experiencing increasing pressure to completely postoperative care pathways within a shorter time frame. The resulting resource, care coordination and change in workflow challenges at BWH led to significant bed-blocking in the post-anesthesia recovery unit (PACU), which also caused operating room (OR) hold ups. In this report, we explored various operations management (OM) methods that can be used to model this bed-blocking problem. Specifically, we conducted a literature review on process mapping, queuing theory, forecasting and regression modeling with emphasis placed on applications to increase efficiency of postoperative care. Additionally, we proposed a number of potential analytical approaches to analyze institutional data from BWH. Preliminary results are also included in this report.

Section 1. Introduction

Our public service operational management challenge deals with delayed discharges, bed-blocking and inadequate staffing of the Post Anesthesia Care Unit (PACU) at Brigham and Women's Hospital (BWH). Surgical outpatients who require an extended postoperative recovery time are monitored in the PACU overnight and are expected to be discharged by 8am the next morning. However, 70-80% of these Extended Recovery Unit (ERU) patients do not get discharged on time for a variety of reasons [Appendix 1]. The delayed discharges in PACU contribute to hold-ups in the Operating Room (OR), which also has upstream impact on the Emergency Department and Inpatient bed outflow. A significant proportion (20-30%) of these delayed ERU patients are also subsequently admitted to the inpatient floor, which creates further bed-blocking problems. Our report will address the the various reasons of and possible operational management solutions from the literatures for this bed-blocking problem, specifically focusing on what can be done from the PACU.

Section 2. Background

With advances in surgical technologies, we are now able to safely perform many operations that used to require inpatient care post-operatively in an outpatient setting, where the patients may be discharged on the same day or after an overnight stay. Over the last decade, for budgetary concerns, Medicare and private insurers have increasingly moved certain elective surgical procedures from an inpatient reimbursement category to outpatient [1]. As a result, a growing number of surgeries are performed at BWH as outpatient day cases (DSU) or outpatient surgery with expected extended recovery period of under 24 hours (ERU).

The number of ERU cases performed at BWH increased by 27% in 2012 and 18% in 2013 [2]. Initially, the ERU patients were still cared for on the inpatient floor overnight, which caused delays in inpatient transfer from the Emergency Department, PACU and outside hospitals. ERU patients overnight stays on inpatient floors had a negative financial impact of $2.7 million for BWH's direct margin in the year 2013 [2], which resulted from a combination of delays in inpatient bed flow and not being reimbursed for the “not-indicated” inpatient stays. BWH responded by housing ERU patients overnight in the PACU since 2014.

However, moving the ERU patients to PACU overnight led to separate bed flow problems as mentioned in the introduction. Additional problems raised by the new care pathway include lower ERU patient satisfaction, clinical concerns for appropriateness of care level for a subgroup of older patients with multiple comorbidities, as well as physician concerns for increased patient risks and professional liabilities due to discharging some patients in a hurry.

Therefore, the operational management solutions must address the ERU challenge both qualitatively and quantitatively.

Section 3. Literature Review on Operations Management Methods

In this section, we explore existing medical, business and operations management (OM) literatures that can be used to address hospital delayed discharges and bed-blocking problems.

3.1 Process Mapping Literature Review

Process mapping is a visual way of representing the workflow that allows the analyst to diagrammatically show the various steps involved in completing a particular project or objective [3]. There are several process mapping methods, mostly developed by the business world, for purposes of cost-accounting, quality control and identifying critical steps, which if shortened can increase workflow efficiencies. In the hospital discharge setting, various types of process mapping techniques have been used to address improvement of patient care pathways, reduce complication rates and increase discharges efficiencies [4, 8].

Process maps usually take the form of some sort of flowchart illustrating how jobs or decision points in a process precede or are dependent on others from start to finish. There are several well known specific ways of constructing a process map and analysing the process. One such example is the Critical Path Method (CPM), which combines information on time taken and sequence involved in completing each step in a process. The path that takes the longest to complete from start to finish is the “critical path” that needs to be shortened to increase the efficiency of the whole process [5]. The CPM was initially pioneered by J.E. Kelley and M.R. Walker in the late 1950’s and subsequently improved upon by many other people.

Other process mapping methods include [6, 7]: Swim-Lane Map, SIPOC (suppliers, input, process, output, customers), Value Stream Mapping, and lately TDABC (time-driven activity-based costing); the latter is similar to CPM. We will focus on the CPM in this report because our aim is to demonstrate a simple way of constructing a process map that captures the complexity of ERU discharge process and also gives useful time-limiting steps information.

The process map for building the CPM is as follows [5, 6, 7]:

1. Select a specific process to map with clear starting and finishing points
2. Plan and select a mapping technique (individual or focus groups interviews)
3. Identify each step in the process (at a high or appropriate level to the processing mapping objectives) and the time it takes to complete it on average
4. Sequence the steps/jobs and determine the immediate predecessors of each step
5. Map the steps/jobs from start to finish as the jobs actually occur - each job is drawn as a circle on the graph, with the job's time and identifying description or symbol. Arrows are used to connect each job from its predecessor(s) to subsequent job(s).
6. Analyse, evaluate and sign off the process map with stakeholders
7. Identify the "bottleneck" or "critical" path for targeting process improvement

The advantages of CPM processing mapping and analysis method include [5]:

- It can be applied in the analysis of a variety of processes and is a very effective way of gaining understanding of existing processes, as well as being helpful in estimating reasonable process costs and completion time.
- The level of detail can be targeted to the particular process improvement objectives
- Able to visually represent very complex processes, like hospital care pathways, which would allow managers and frontline staff to better identify problems and solutions
- It identifies the "critical" path and steps that need to be improved hence help prioritise additional process improvement resources
- Gives opportunities for qualitative analysis of the interviews conducted to construct the process map. Qualitative analysis can often identify patterns and causes of process delay, giving additional perspectives that sometime can not be captured by quantitative and process mapping analyses alone.

The disadvantages include [5]:

- It can be a resource intensive exercise, particularly for complicated hospital patient care pathway processes. Estimate or measuring the time taken for each step/job in the process is time consuming and may be fraught with error.
- It may not be able to capture all the different and dynamic ways that nursing, MD, and various coordinators interact with each other to get the same process completed. This

contributes to the resource intensiveness if one aims to capture all the minutiae. A higher level mapping with less detail is often more plausible but may lose important detail.

- CPM is also not supposed to be used for cyclical processes

3.2 Queueing Theory Literature Review

Queuing theory is the mathematical study of waiting lines with wide applications in engineering and industry. Queues are ubiquitous in healthcare. From a specialty perspective, queuing theory has been applied in cardiac care units [1], obstetric services [2], operating rooms [3, 4] and emergency departments [5]. Recently, queuing theory framework has been applied to an even broader range of healthcare activities [6-8]. In terms of utility, queuing models have been used to better understand waiting time and utilization, systems design and appointment systems at scales ranging from individual units to regional health systems [9].

In surgery, there are several notable studies that have successfully used queuing theory. Tucker et al. applied the basic single-phase, single-channel formula to model patient utilization of OR services. By calculating the probability of two more or cases occurring simultaneously on night shifts, they determined that the activation of a second OR team when the first team is busy on night shifts is unnecessary [4]. Paul et al. used a non-preemptive multi-priority queuing model and discrete event simulation to calculate the required number of emergent OR for a hospital surgical department and appropriate pricing based on priority level [10].

Similarly, a number of studies have applied queuing theory in intensive care unit (ICU). McManus et al. utilized an M/M/c/c model to predict admission turn-away rates for a busy, urban ICU and found that the calculations correlated highly with observed data [11]. Finally, Hagen et al. examined different queuing models for five urban ICUs and effects on wait times, utilization, return rates, mortalities and number of patients served. They concluded that prioritizing patients by severity considerably reduced delays for critical cases, but also increased the average waiting time for all patients. Aggressive bumping significantly raised the return and mortality rates, but more conservative methods balance quality and efficiency with lowered wait times without serious consequences [12].

Study by Schoenmeyr et al. is most relevant to our project. They modeled the dynamics among OR and PACU as a function of the number of recovery beds, surgery case volume, recovery time and other parameters [13]. They created a modified M/G/∞ queue to model the flow of patients through a congested PACU in which jobs (patients) arrive to the servers (staffed beds in PACU) to be served (recover from anesthesia). Since patients start their recovery from anesthesia after emergency regardless of whether there is an available bed in the PACU, the authors adapted the model to assume there are infinitely many servers and created "real" (actual PACU beds) and "dummy" (waitlist slots for patients recovering in the OR) servers.

Next, they tested the underlying assumptions of the model using actual OR data and simulation experiments and determined that actual PACU arrival data is congruent with exponentially distributed inter-arrival time, and this held true for hypothetical OR suites between 5 and 50 ORs in size. To ensure this assumption holds for other hospitals, the authors surveyed scheduling practices at 32 other large hospitals and found that there were no scheduling policies in place that would lead to non-random arrival rate into the PACU. Once the assumptions were validated, the queuing model was used to predict the number of additional beds required to eliminate the wait list for PACU.

This study by Schoenmeyr et al. set an example of how queuing theory can be applied to the flow of patients from OR to the PACU. We will adopt a very similar approach in creating our own queuing model of the BWH PACU to better understand the bed-block and capacity problem with real data. The queuing analysis can be found in Section 4 of this report.

3.3 Forecasting Literature Review

Most of the literature regarding PACU forecasting focuses on what we might call "micro-forecasting" – i.e. predicting demand and scheduling needs within the next 6 - 48 hrs. According to Ryckamn et al. 2009, in one pediatric hospital, surgeons predicted a length of stay (LOS) for each patient simply based on their expert opinion. This was then paired with a system where whenever a surgery was scheduled, a recovery bed also had to be scheduled simultaneously, with the LOS predicting how long the bed would be occupied. Staff would closely monitor projected bed occupancy rates, and would redirect patients or reschedule surgeries once the beds were expected to be filled. To help make the recovery bed occupancy rates more predictable, the hospital also limited the number of elective surgeries (its biggest sources of variability) that it would accept each day.

Yancer et al., 2006 saw a similar system set in place where twice daily census meetings looked at admission and discharge projections, and current bed availability. This was used to keep the nursing director aware of both the quantity and intensity of patients needing care in the PACU. This allowed the nursing director to identify mismatches in supply and demand before they occurred, and create strategies to relocate patients or handle an overload capacity before it occurred. They also did an annual forecast that lead them to create recovery beds at a nearby facility handle excess seasonal demand.

Other forecasting systems became more specific in how they classified the qualitative state of each patient in order to more precisely predict staffing demands. Soutar et al. 2000 describes a system where patients are classified by complexity and intensity on a five tiered scale. Nurses are then allocated based on the projected needs. For instance, nurses could oversee three Class 1 patients, two Class 2-4 patients, or one Class 5 patient. This would allow more accurate forecasting of how many nurses would be required at a given time, and would help reallocate PACU resources during the day. Dexter et al. 2006 also confirms that such forecasting methods are effective for adjusting staff allocations more efficiently, rather than sticking to the general one nurse to two patients ratio.

3.4. Regression Modeling Analysis literature review

Specific to outpatient or ambulatory surgery, multiple regression in health care has been applied to models predicting delays between admission and time of operation[1,2] surgical case duration[3] and which pre-existing medical conditions lead to adverse events and therefore potential delayed discharge or admission.[4] Studies using regression to focus on unanticipated discharge all cite a key prospective study in the 90s.[5] This highlighted the incidence of predictive factors for unanticipated admission following ambulatory surgery. Subsequent studies have used this for benchmarking to ascertain if their rates are excessive. Two key papers for the purpose of our analysis are a retrospective case control study and a prospective study.

The prospective study used data from over 15,000 patients and modelled a time to discharge variable that was logarithmic using surgery, patient and anesthesia variables.[6] A log function was used due to a skewed distribution regarding discharge time. The results showed that the type of surgery particularly those that increase risk of postoperative nausea and vomiting or significant pain and the strongest association with length of stay. Monitored anesthesia care (i.e. not general anaesthesia) was associated with a shorter stay, but patients with congestive heart failure specifically had an increased risk of a longer stay.

The retrospective study looked at 400 procedures performed logistic regression looking at demographic surgical, and anesthesia delivery factors.[7] To compare patients who had unanticipated admissions to those who did not. The odds ratios were used for analysis, and multiple imputation for missing data. This provides an assessment of the impact that of missing data on the results. Surgical complications were the single most common cause for admission. Factors such as age, American Society of Anesthesiologists (ASA) Physical Status classification (a clinical measure of the 'fitness' of a patient assigned by an anesthesiologist) and BMI were also predictive. Also the type of surgery also had an impact, with orthopedic, dental and upper airway surgery, having a reduced risk when compared to general surgery. Interestingly both Canadian studies showed that in patients receiving general anesthesia, smokers had a shorter stay compared to non-smokers.

Section 4 Proposed Analysis - Application to the ERU challenge

In this section, we outline our OM analysis proposals and actual analyses in cases where we have managed to collect data, with help from Dr. A. Bader and R.N. L. Morrissey.

4.1 Process Mapping Analysis and Qualitative Interview Results

Following the CPM described in Section 3.1, we interviewed the people involved in discharging ERU patients at BWH (PACU nurses, administrators, attending MDs and surgical residents) to identify the main steps involved in discharging an ERU patient. We arrived at a process map table [See Table 1 in Appendix for the full CPM table], which could be converted into an actual process map if only we had enough resources to gather all the time information (only examples of rough time estimates in this table).

Job No.	Description	Immediate predecessor(s)	Normal time (hours)	e.g. URO time if different	e.g. GYN time if different
a	Start - OR finishes		0		
aa	Transfer to PACU	a	0.2		
b	PACU status phase I to II (Independent airway and alert)	aa	2		
c	Transfer to ERU care category (in PACU)	b	e.t.c		
: :	: :	: :	: :		
y	Finish - ERU patient out of PACU bed	u, v, x	0		

Due to the lack of time information for all the steps, we are not able to identify the "critical path". However, the interviews allowed us to analyse general and specialty specific reasons that delay ERU discharges qualitatively:

- *General reasons:*
    - Lack of ride home in the morning - due to no family members available or more commonly to busy Boston morning traffic so family unable to arrive by 8am.
    - Some patients are just not suitable for ERU care only post-operatively due to their complex background comorbidities, which means they are likely to have problems with stabilising blood pressure, poor O2 saturation, and unsafe mobility, etc, post-operatively. Discharging them prematurely from PACU by 8am the day after operation exposes both the patients and their surgeons to unwanted risks. Unfortunately, at the moment, the post-operative care category for a patient is determined by the insurance pre-operatively and is mostly based on procedural codes only, taking insufficient consideration for patient risk factors.

- *Specialty specific reasons for the top 4 specialties with delayed ERU discharges:*
    - Urology and gynecology - commonly delayed by failed morning trial of void for patients who had temporary catheters post-operatively
    - Plastic - Many are private patient expects Attendings to review them on day of discharge even though this would not change management and residents could easily discharge them on time. Also, sometimes due to wound and drain problems
    - Gastroenterology - Need to make sure patient can eat or drink during breakfast, which can delay discharge if patients did not get up early enough

The specialty specific delay causes could help us target the CPM process map for individual specialties (e.g. see column 5 and 6). With right organizational leadership, resources and communication, we could addressed these areas first and re-assessed for effectiveness.

4.2 Queueing Theory

Any delays in PACU discharge, either from ERU or patients waiting to be admitted to inpatient beds cause strains on PACU beds and nursing resources. The strain is mostly on the most nursing intensive Phase I stage of PACU patient care pathway, i.e. the PACU delays reduce the number of "servers" (nurses) available to take on the Phase I care of new post-op patients from the OR. This in turn causes OR hold-ups, i.e. increases the wait time in the "queue". We managed to get over three months (1st Nov 2015 to mid-Mar 2016) of OR and PACU time-stamped data through BWH's EPIC system, which we have used to model this critical part of the post OR queue through PACU (See red box in the Appendix 2).

From EPIC, we obtained the following time-stamped data in chronological order:

- In.Room.Time - Patient in OR room
- Patient.Ready.Time - Patient ready for OR, on the OR table, etc
- Procedure.Closing.Time - e.g. Closing up wound, coming to end of surgery
- Procedure.End.Time - End of procedure
- Ready.for.Recovery.Time - end of anesthesia and patient ready to move to PACU
- Out.of.Room.Time - Patient left the OR room
- In.Phase.I..PACU..Time - Patient arrived in PACU and handed over the Phase I nurses
- Phase.I.Care.Complete..PACU..Time - Patient alert and independent with airway
- Out.of.Phase.I.Time - moved from Phase I to II, waiting to be discharged out of PACU
- Procedural.Care.Complete.Time - Patient physically discharged out of PACU

The definitions of arrival rate, server time and capacity we used are as follow:

- Arrival rate, lambda = number of patients becoming "Ready.for.Recovery.Time" per hour = total number of patients in dataset / total number of operating hours over the weekdays = total number of patients in dataset / (sum of [max(Out.of.Room.Time) - min(In.Room.Time) on each day] over all the days)
- Server time, 1/mu = 1/average_time(Out.of.Phase.I.Time - Ready.for.Recovery.Time)
- Capacity, c = number of PACU nurses available to staff the Phase I care

We performed the analysis of the raw data in R. For detailed analysis please see the separate R output file submitted with the report. Here are the empiric results (weekends removed) for:

- Arrival rate = 3.1978 per hour

- Average service time throughout a day, 1/mu = 3.718 hours
- Service rate = 0.269 per hour

If our goal for the queueing model is to find out the optimal number of "servers" (nurses) that should staff the PACU Phase I care, we would also need to have more information on the hourly cost of a PACU Phase I nurse as well as the opportunity cost of each minute of OR hold-up time. The objective of the optimization would be to minimise the total costs.

Limitations of our model - questions and alternatives to consider:

1. What are the actual distributions of lambda and mu, which matter for calculating c. We could probably check this by plotting the distribution of lambda and mu from day to day, and comparing the mean with the variance.
2. Data quality of EPIC time-stamp data - this should be considered as EPIC was only introduced at BWH in May 2015. The entry of time-stamp data is done manually so there is some variability in the quality or reliability of data. We pulled data after 6 months of EPIC use at BWH - so that most staff are familiar with the new system by then. We also only chose variables that have low missing-value rate (more reliably entered)
3. The PACU nursing staff are actually staggered throughout the day based on rough historical estimate of OR output load at different times of the day - this complicates our model as the service capacity changes throughout day (and logically works best this way), which in turn means our average service time throughout a day is only a very rough estimate. Up to 10-15 last minute OR scheduling or cancelling can occur in any one week, which makes accurate prior PACU staffing difficult. One possible alternative OM method to plan PACU nurse staffing would be to do a more modeling of OR output by the hour on day to day basis and see how well the current staffing algorithm is in covering the hourly demand (much like the ED staffing case shown in the class).
4. From the interviews with nurses and surgeons, we found out that different weekdays have different OR output loads and on some days (e.g. Wednesday) the whole schedule is delayed due to institutional wide Grand rounds (staff teaching) in the morning.
5. The actual staffing of PACU nurses is very complicated, which we have not taken account of in our simple queueing model. There's a general pool of PACU nurses (10-14

in the morning) to look after all PACU and ERU patients. However, if DSU or Pre-op nurses are overloaded in the morning (which is very common), PACU nurses get pulled away temporarily to help them - but the reverse is often not true when PACU is very busy because most DSU and Pre-op nurses are not highly trained enough to take care of the more complicated Phase I PACU patients.

4.3 Proposed Forecasting Approach

The problem we are trying to address at BWH is slightly different than the problems usually studied in the PACU literature, but many of these techniques can still be applied. For instance, one of the reasons patients are not released on time is they do not meet the minimum set of post-operative medical requirements required to leave. Based on the expertise of the surgeons or nurses who admit patients to the PACU, some of the more problematic cases likely to cause delays the next morning may be identified. This would then turn into a forecast for the following morning describing how many medically problematic cases are likely to exist and where. This could then help the new morning nursing allocate their time more efficiently. Using a scaled patient classification system similar to Soutar et al. 2000, more fine-grained predictions may even be possible, which could also lead to more efficient staff allocation.

However, Brigham and Women's benefits from having enough data to likely go beyond simply expert opinion for their short-term forecasts (footnote[1]). For each delayed PACU case, data exists describing the type of surgery, length of delay, primary cause of delay, and more. They also have data on the PACU cases that were not delayed for comparison. That means creating multivariate regression models could be a better way to describe which patients are more likely to cause delays than expert opinion as described above. Or they could possibly be used in conjunction with expert opinion.

[1] Epstien et al. 2002 found their models for PACU staffing improved up to 100 work days of data, but not beyond. However, this number can only be used as a loose estimate given varying parameters between models.

This data also is useful in that it can tell us *why* a patient is likely to be delayed (see Appendix 3). Initial data suggests that some types of surgery are delayed more often for work up reasons, which the nurses in the PACU may actually be able to address. However, other types of surgery are more likely to have delays created by the surgeon or the personal reasons like the patient's ride coming late. Even if the hospital cannot change the factors that cause these delays, a multivariate regression model could at least smooth the burden for the nurses. For instance, sometimes the nurses are stuck with many patients that all require extra care to get them out on time. While at other times, they disproportionately have patients who are delayed for issues not at all related to the nursing staff's capacity. If the forecasting model could be used to make sure there was usually a balance of patients that did and did not need extra nurse staff attention, that alone could improve the delay rates.

Additionally, the initial data suggests we could also make effective use of chronological forecasting. First, annual cycles may occur (appendix 4) that could be matched with changes in staffing allocation over time. This type of forecast would likely best be created using exponential smoothing with annual seasonality. Differing alphas and gammas would be tried in the model. Then the values that produced the lowest mean absolute deviance (MAD) and/or mean absolute percentage error (MAPE) for the existing data would be used to forecast future months.

Weekly forecasts could also be useful given there seems to be some trends in the initial data there as well (see appendix 5). A simple regression model would tell you which days are most prone to delays, and you could then allocate more staff on those days. But that may be too simple because we still are unsure of the causality relationship between time and type of surgery. If vascular surgeries are usually on Tuesday, a day with lots of delays, is it because vascular patients tend to be late and make Tuesdays look bad? Or is it because Tuesdays are understaffed causing the vascular patients to leave late? Qualitative evidence, schedule histories, and careful economic analysis would likely be needed to fully tease that issue apart. Otherwise many proposed solutions may target the wrong issue.

4.4 Regression Modeling Proposed Analysis

Patient data from EPIC at BWH provides patient and surgical procedure specific variables for retrospective and prospective analyses. The outcomes of regression analyses can be used to stratify patients for their suitability for ambulatory surgery. BWH already has a preoperative anesthesia (Weiner) center, which would be the ideal place to implement protocols. Intraoperative protocols can be established for patients undergoing operations with high risk of postoperative pain, nausea and vomiting to minimise effects. Finally, particular higher risk operations or subspecialities of surgery may require scheduling at the beginning of the day, to provide greater post-operative time for recovery. Previous studies have shown variation in some of the surgical subspecialities that prolong stay, suggesting that unspecified local factors are likely to provide unique results for consideration.

Section 5. Conclusion

In this report, we defined causes and the current state of the bed-blocking problem in the BWH PACU. We have conducted a literature review on process mapping, queuing theory and forecasting to find existing operational management methods in optimizing postoperative care. Based on the results of the literature review, we proposed a number potential analyses and produced preliminary models using real-life data from BWH. We hope to continue this analysis with additional data with the goal of generating specific recommendations for BWH to alleviate its PACU bed-blocking problem.

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Section 7. Appendix

Appendix 1: List of common reasons delaying ERU discharges

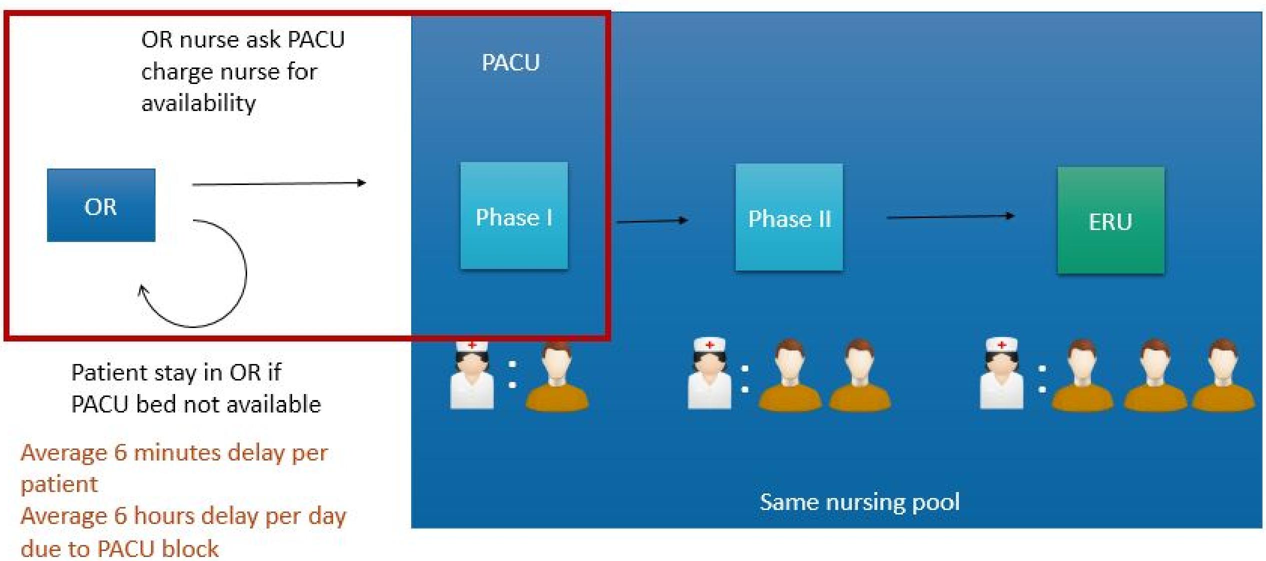
- No ride home or ride not on time due to morning traffic
- Late MD (residents) evaluation and completion of discharge orders
- Ensuring safety i.e. voiding trial, tolerating food, managing wound care
- Finishing IV meds or waiting for blood results to come back
- Physiotherapy/Occupational Therapy assessment left until the morning
- Liaising/setting up outpatient follow up
- Inadequate PACU staffing in the morning

Table 1: CPM for ERU patient discharge process

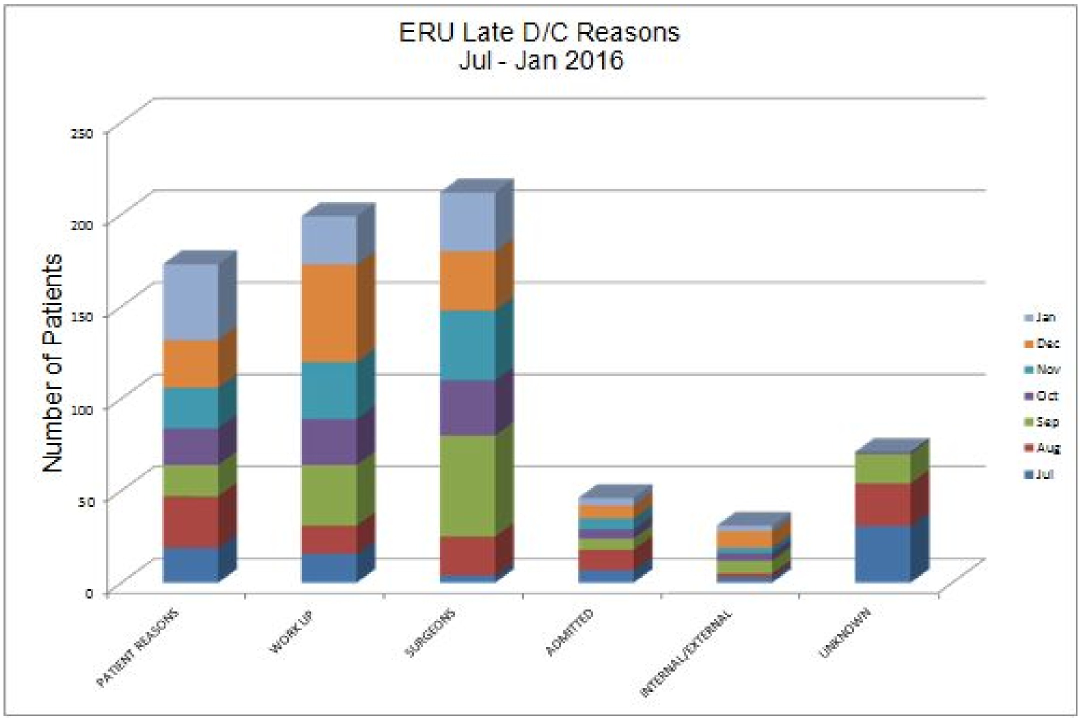
Job No.	Description	Immediate predecessor(s)	Normal time (hours)	e.g. URO time if different	e.g. GYN time if different
a	Start - OR finishes		0		
aa	Transfer to PACU	a	0.2		
b	PACU status phase I to II (Independent airway and alert)	aa	2		
c	Transfer to ERU care category (in PACU)	b	0.1		
d	Post-op education for patient, and family if present	b	etc		
da	Confirm morning 8am discharge time for pick-up/ride status	d			
e	Pain and nausea control and complete post-operative medications	b			
f	Stabilize and monitor Vital Signs overnight in ERU (e.g. BP, O2 saturation, BSL)	b			
g	Finish IV medications (e.g. antibiotics, anti-hypertensive, opiods analgesia)	e, f			
h	Establish normal eating and drinking	b			
i	Check walking/mobilising safely	c			
ia	Physiotherapy review if has mobility safety concerns	i			
j	Social work review if has social concerns	c			
k	Check if passing urine normally	c, h			
l	Morning backfill trial-of-void (TOV) if has temporary IDC post-operatively	c, k			
m	Recatheterisation if failed to pass urine 30 minutes after TOV	l			
n	Catheter/IDC care education if going home with temporary IDC	m			
o	Wound and dressing care if required	c			
p	Nurse books VNA if require outpatient nursing care	o			
q	Morning MD (surgical resident) review for medical clearance for discharge	e, f, h, I, j, k, l			

r	MD complete discharge order if clinically cleared to go home	q			
s	Nurse checks with patient if ready for discharge and offer further education if required	q			
t	Nurse confirms discharge criteria met	d, g, ia, n, p, r			
u	Patient discharge with ride or taxi voucher if qualifies	t			
v	Patient discharge to waiting area if clinically safe but ride has not arrived	t			
w	Patient admit to inpatient order if clinically indicated (e.g. complication, pain, etc)	q			
x	Transfer patient to inpatient floor	w			
y	Finish - ERU patient out of PACU bed	u, v, x	0		

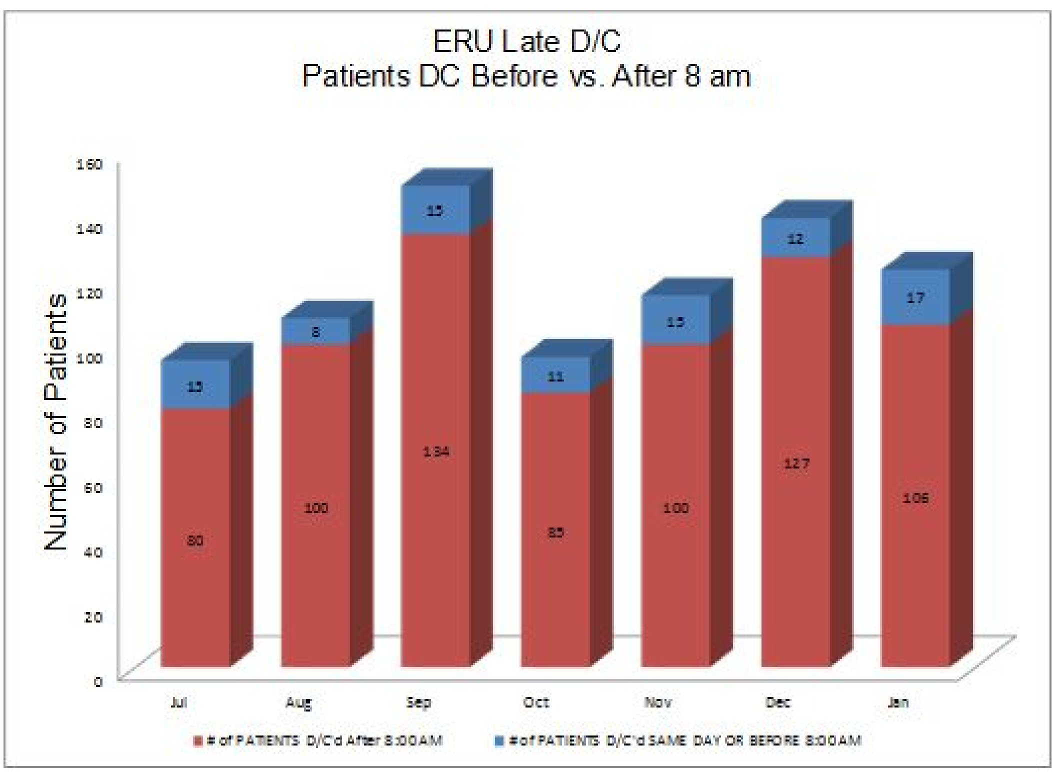
Appendix 2. Queuing mode (see red box)



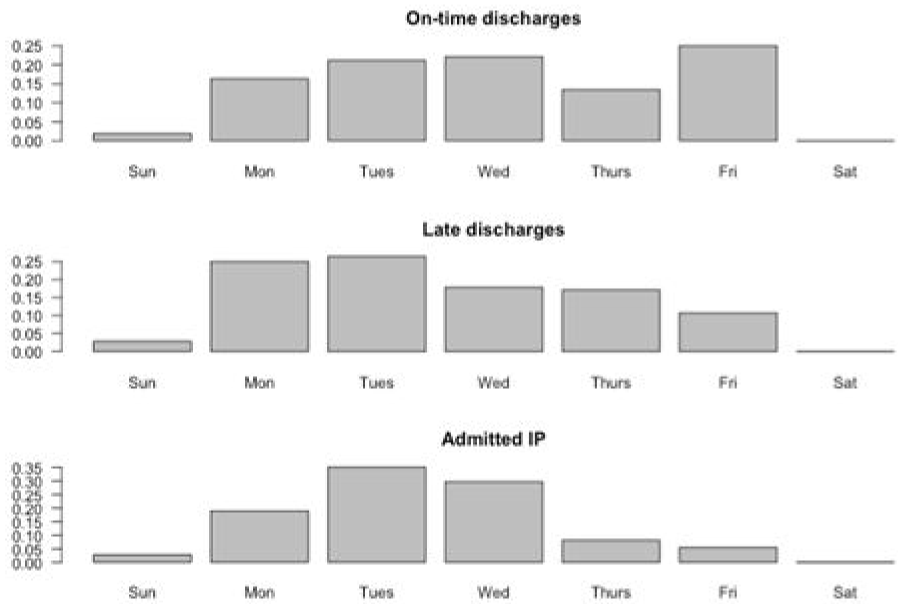
Appendix 3 (Data from BWH)



Appendix 4 (Data from BWH)



Appendix 5 (Data from BWH)



Appendix 6 Process Mapping Figures

Figure 6.1. Surgery Patient Flow

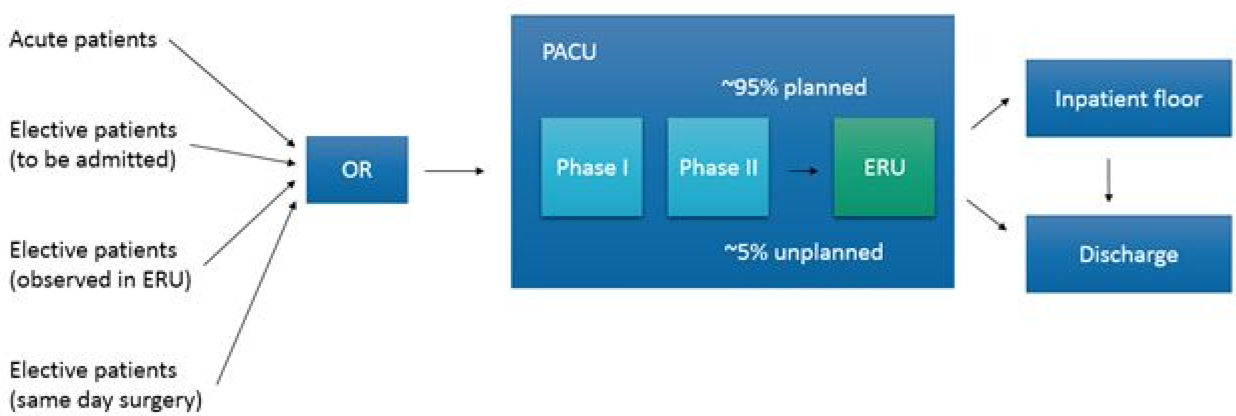


Figure 6.2. Flow of ERU Patients

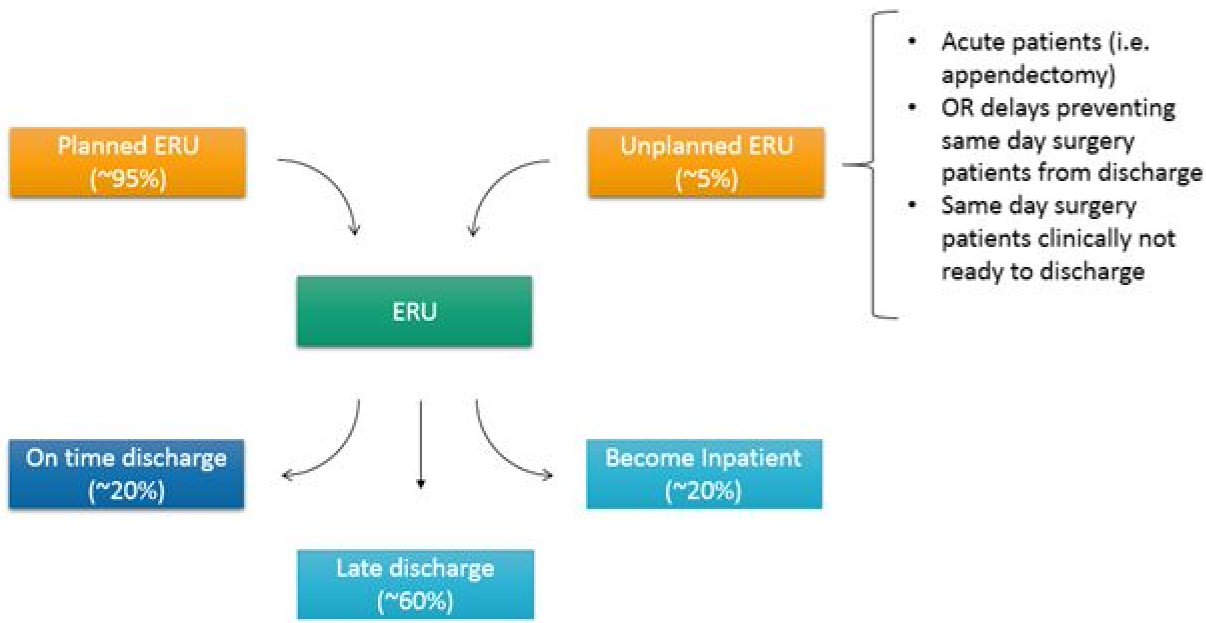


Figure 6.3. ERU Discharge Procedure

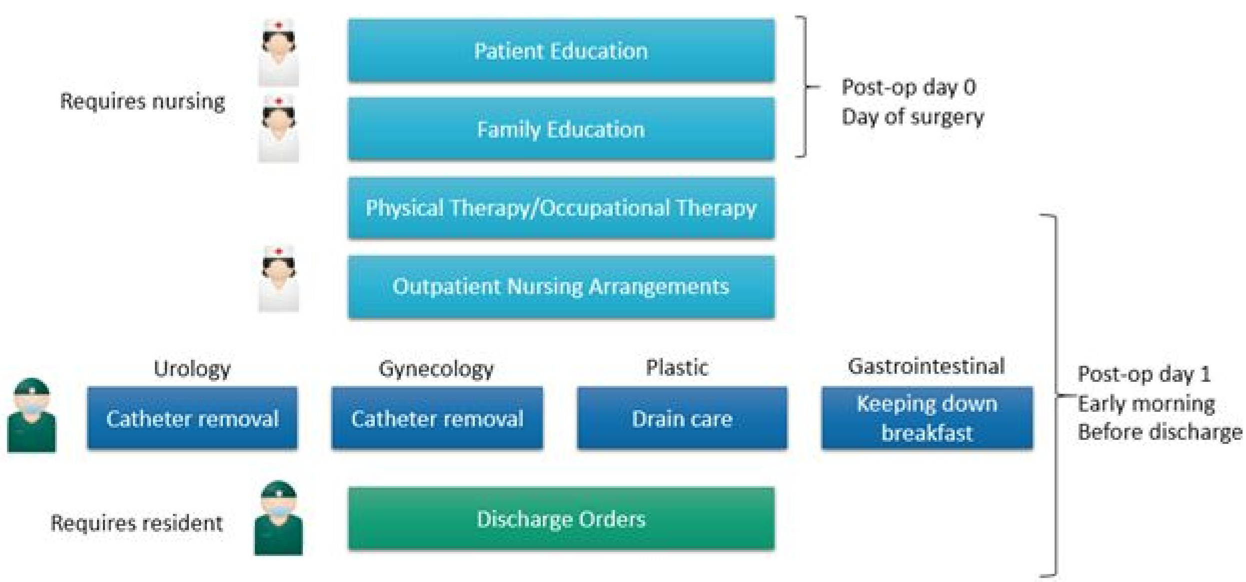


Figure 6.4. Resident Morning Workflow

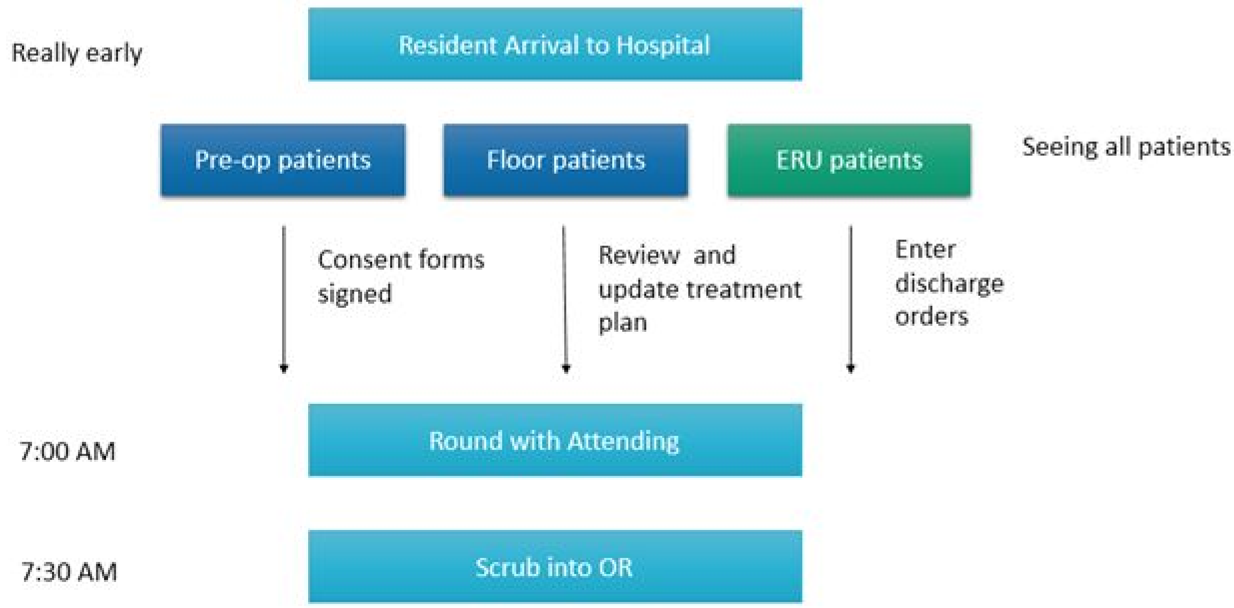


Figure 6.5. OR to PACU Patient Handoff