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Research

Patient-specific Predictors of Surgical Delay in a Large Tertiary-care Hospital Operating Room

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A B S T R A C T

Purpose: The purpose of this study was to describe patient-specific factors predictive of surgical delay in elective surgical cases.
Design: Retrospective cohort study.
Methods: Data were extracted retrospectively from the electronic health record of 32,818 patients who underwent surgery at a large academic hospital in Los Angeles between May 2012 and April 2017. Following bivariate analysis of patient-specific factors and surgical delay, statistically significant predictors were entered into a logistic regression model to determine the most significant predictors of surgical delay.
Findings: Predictors of delay included having monitored anesthesia care (odds ratio [OR], 1.28; 95% confidence intervals [CI], 1.20-1.36), American Society of Anesthesiologist class 3 or above (OR, 1.21; 95% CI, 1.15-1.28), African American race (OR, 1.25; 95% CI, 1.12-1.39), renal failure (OR, 1.20; 95% CI, 1.09-1.32), steroid medication (OR, 1.13; 95% CI, 1.04-1.23) and Medicaid (OR,1.18; 95%CI, 1.09-1.30) or medicare insurance (OR, 1.14; 95% CI, 1.07-1.21). Six surgical specialties also increased the odds of delay. Obesity and cardiovascular anesthesia decreased the odds of delay.
Conclusions: Certain patient-specific factors including type of insurance, health status, and race were associated with surgical delay. Whereas monitored anesthesia care anesthesia was predictive of a delay, cardiovascular anesthesia reduced the odds of delay. Additionally, obese patients were less likely to experience a delay. While the electronic health record provided a large amount of detailed information, barriers existed to accessing meaningful data.

Despite only a quarter of hospital stays requiring an operating room (OR) procedure, almost half of the $187 billion spent in American hospitals per year is for hospital stays that involve an OR procedure.[1] Per minute OR costs range from $36 to $37 on average for private and public hospitals in California,[2] and up to as high as $150 in one New York City hospital.[3] Because of these high costs, hospitals often seek ways to reduce surgical delays and cancellations in an effort to improve efficiency.[4–7] Occurring in 14% to 95% of surgical cases (depending on the sample), surgical delay is a principal cause of health care inefficiency.[7–9] It not only adds financial cost, but can also have a negative impact on patient satisfaction and clinical outcomes in emergency surgeries.[10–12]

The causes of surgical delay are numerous and vary widely among studies and institutions. Facility-specific factors can comprise staff, equipment, and room availability. Other miscellaneous reasons are often administrative in nature such as insurance, payment, or informed consent procedures. Patient-specific factors that have been studied include availability and general health status.[5,7,13–15]

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Based on early research demonstrating the effectiveness of preoperative clinics in preventing surgical delay through optimization of patient health status, a commonly held belief is that sick patients are more likely to be delayed than healthy patients.[16,17] Contradictory to this presumption, a large retrospective study of medium-sized community hospitals with 497,205 cases found patients with an American Society of Anesthesiologists classification of three or greater (indicating a higher chronic illness burden) had a decreased odds of being delayed.[8] Furthermore, while this study examined the effect of overall chronic illness burden via American Society of Anesthesiologists (ASA) classification on surgical delays, it did not look at specific disease processes that may cause delay.

Another issue to consider is that first-case starts should be differentiated from delays that occur later in the day. First-case starts are the first surgical cases of the day. Cases that follow the first case of the day are more likely to be delayed because of prior cases running later than expected and times needed for OR turnover.[18] For example, when Deldar et al[5] implemented a Lean performance improvement process to improve first-case starts, specifically, patient-specific factors were central to their evaluation including preoperative preparation and assessment, imaging or patient work-up requirements, medications, and patient or family late arrival to the hospital.[5]

A potential tool to capture variations in clinical approaches, patient factors, and institutional protocols is to use data captured in the electronic health record (EHR). Given the large volume of captured information as well as the general integration of EHRs among various health care institutions, EHR data affords the potential for large-scale exploration of myriad health care trends. The data must be used cautiously and with recognized limitations such as heterogeneous categorization, variation in system definitions, and frequently incomplete records.[19] In some instances, the data may not have needed granularity and thus patient-specific factors are lost or hidden within other factors contributing to delay. In other studies, patient-specific factors are found embedded in several of the categories used to describe surgical delay, rather than categorizing all patient-specific causes together.[5,20]

While there is evidence that the patient plays a role in surgical delays, the significance of patient health status is not fully understood. More specifically, there is a limited explanation of the types of patients or patient-specific factors that might contribute to a surgical delay. Thus, to better understand the role of the patient in surgical delays, the present study sought to describe which patient-specific causes are correlated with surgical delay using readily available data in the EHR.

Methods

Data Source

Data of patients who underwent surgery in a large, tertiary-care academic hospital were retrospectively extracted from the EHR from May 2012 through April 2017. The facility tracked patients receiving surgery in the main hospital as a part of a surgical quality improvement project and created a database for analysis that included age, date and time of surgery, ASA classification, surgical specialty, anesthesia type, and admission status. Because the data were retrospective, the study was exempted from informed consent requirements and qualified for expedited review through the Institutional Review Board.

The dependent variable, surgical delay, was defined as any delay in the start of surgery of 1 minute or greater from the scheduled time, consistent with this facility's definition of a surgical start delay. Cases that started at the scheduled time or earlier than the scheduled time were defined as the reference category.

Independent variables included patient characteristics, anesthesia type, surgical specialty, comorbidities, and medications. Variables not initially collected on the date of surgery were retrospectively extracted from the patient profile section of the EHR for each patient. To gather comorbidity and medication data, ICD-9[21] and ICD-10[22] diagnosis codes were used initially. Due to the large amount of missing data with this method, keyword search terms were used instead to query the EHR for comorbidities (Table 1) and home medications (Table 2).

Patient characteristics included age, gender, ethnicity, race, health plan, distance from the hospital, ASA classification, and admission status. Distance from the hospital was calculated using Google Maps to determine the number of miles between the patients' home zip code and the hospital.[23] ASA classification was based on the definition of the American Society of Anesthesiologists.[24]

Health status was described using comorbidities and home medication use. Comorbidity variables included 27 of the most common chronic diseases and conditions that were identifiable in the EHR. Medication variables included the 10 most common medications used for chronic illness management that were prescribed to the patient at the time of surgery and a numerical count of the prescribed medications as a proxy measure of health status. Comorbidities and medications of interest were identified by three anesthesia providers with more than 10 years of experience each in academic surgical settings.

Duplicate data entries were discovered secondary to patients having multiple surgeries within the 5-year study timeline. For analysis purposes, only the first surgery for each patient was included in the dataset. Emergency cases were excluded due to the difference in scheduling rules from routine cases, as it is generally accepted that emergency cases must proceed even if there are missing surgical prerequisites. While data were included from May 2012 through April 2017, there was a total of 2 months of missing data that was omitted from analysis due to the failure of surgical start time recording. Furthermore, any case with missing data for the variables of interest were excluded from analysis.

Data Analysis

IBM SPSS for Macintosh v. 25 was used for statistical analysis of the data.[25] Descriptive statistics were used to describe the surgical patient population as a whole. Further exploration of the differences between patients that experienced a surgical delay and those who did not in the context of the patient-specific variables was completed (Table 3). All continuous patient-related variables (age, distance, and number of home medications) were analyzed for normality. Any normally distributed continuous variables were analyzed using a Student's t test and non-normally distributed continuous data were transformed to categorical data. Significance was set at $P < .01$. Those dyads showing significance were entered into a logistical regression model with odds ratios and 95% confidence intervals (CI). Admission status was entered into the model because of the substantial difference in the way patients are prepared for surgery based on this variable. The surgical specialty was entered into the model because of its strong significance in bivariate analysis.

Results

There was a total of 55,233 surgical cases in the original dataset. After the application of exclusion criteria, 32,818 cases remained. In the final sample, 16,675 (50.8%) of all cases throughout the surgically scheduled day were found to be delayed. Delays of the first case starts comprised 21.9% (n = 3,651) of total delays. Delay times ranged

Table 1
Comorbidity Variables Definitions

Comorbidity variable	Keyword search terms
Hypertension	Hypertension, High Blood Pressure
Heart failure	CHF, Heart Failure, Cardiomyopathy
Coronary artery disease	Coronary Artery Disease, Myocardial Infarction, Chest Pain, Angina
Arrhythmia	Atrial Fibrillation, Ventricular Fibrillation, Ventricular Tachycardia, Heart Block
Pacemaker or ICD	Pacemaker, Implantable Cardioverter Defibrillator, ICD (internal cardiac defibrillator)
Vascular disease	Peripheral vascular disease
Renal failure	Kidney Failure, Renal Failure, Dialysis, Chronic Kidney Disease, Renal Insufficiency
Liver failure	Liver Failure, Hepatic Failure, Cirrhosis
Gastrointestinal reflux	GERD, reflux, Heartburn, Hiatal Hernia
Diabetes	Diabetes
Hypothyroidism	Hypothyroidism
Anemia	Anemia
Musculoskeletal	Arthritis
Chronic pain	Fibromyalgia, Chronic Pain, Neuropathy, Migraine
Psychological	Depression, Anxiety, Bipolar, Schizophrenia, Psychosis
Cancer	Tumor, Leukemia, Lymphoma
Obesity	Body Mass Index >30

Table 2
Medication Variable Definitions

Medication variable	Keyword search terms
Insulin	Insulin
Hypoglycemic	Glipizide, Glyburide, Metformin, Actos, Pioglitazone, Acarbose, Nateglinide
Antihypertensive	Atenolol, Labetalol, Metoprolol, Propranolol, Carvedilol, Lisinopril, Enalapril, Captopril, Hydrochlorothiazide, Losartan, Valsartan, Amlodipine, Nimodipine, Nifedipine, Clonidine
Antiarrhythmic	Diltiazem, Verapamil, Amiodarone, Sotalol
Steroid	Prednisone, Prednisolone, Methylprednisolone, Hydrocortisone, Dexamethasone, Triamcinolone
Anticoagulant	Warfarin, Heparin, Rivaroxaban, Dabigatran, Apixaban, Edoxaban, Enoxaparin, Fondaparinux, Clopidogrel, Ticagrelor, Dipyridamole, Aspirin, Ticlopidine, Eptifibatide
Opioid	Codeine, Fentanyl, Hydrocodone, Oxycodone, Meperidine, Hydromorphone, Methadone, Morphine
Antidepressant	Fluoxetine, Duloxetine, Amitriptyline, Desipramine, Nortriptyline, Imipramine
Antipsychotic	Clozapine, Olanzapine, Quetiapine, Risperidone
Antianxiety	Alprazolam, Clonazepam, Diazepam, Lorazepam

from 1 to 1318 minutes with a median of 44 minutes and an interquartile range of 79 minutes (Figure 1). The average age of all patients sampled was 58.2 years. The bivariate analysis demonstrated several patient characteristics that exhibited significant differences between delayed patients and those that were not delayed (Table 3).

The final logistic regression model revealed seven patient-specific variables that were statistically significant for an increased odds of delay and two variables that were statistically significant for decreased odds of delay (Table 4). Variables that were significant in bivariate analysis, but did not predict delay when entered into the model included age, ethnicity, medication count, distance from the hospital, as well as most medication and comorbidity variables. There were 6 surgical specialties that had increased odds of delay compared to the reference category (Table 5). The overall model accounted for 3.7% to 4.5% of surgical delays in this sample by Cox-Snell and Nagelkerke pseudo R-squared analysis, which accounts for the amount of variance that is explained by the model. The model had a 46.7% predictive rate for being on-time, a 65.2% predictive rate for delay, and an overall predictive rate of 56.1%.

Discussion

The findings from this analysis contribute additional information about the specific types of patients who may be at risk for a surgical delay. Based on prior studies, one area in need of clarification is whether patient acuity or chronic disease burden is predictive of surgical delay. In the current surgical patient sample, patients with an ASA classification of three or more, indicating severe chronic illness that is not well-controlled, had a 1.21 ($P < .001$) greater odds of delay. One possible explanation for this finding, which contradicts

Table 3
Descriptive Analysis of Surgical Patients

	On-time n (%)	Delayed n (%)	*P*-value
Mean age (years): 58.18 (std. dev. 16.32)	58.08 (std. dev. 16.36)	58.27 (std. dev. 16.28)	< .001[*]
Gender			.042[†]
Male[‡]	8,721 (26.6)	8,822 (26.9)	
Female	7,422 (22.6)	7,853 (23.9)	
Hispanic ethnicity			< .001[†]
Not Hispanic[‡]	12,764 (38.9)	12,933 (39.4)	
Hispanic	3,379 (10.3)	3,742 (11.4)	
Race			< .001[†]
White[‡]	11,127 (33.9)	11,082 (33.8)	
Asian	1,380 (4.2)	1,417 (4.3)	
African American	680 (2.1)	902 (2.7)	
Other race	2,956 (9.0)	3,274 (10)	
Health plan/insurance			< .001[†]
Managed care/exchange[‡]	7,849 (23.9)	7,398 (22.5)	
Medicare	6,629 (20.2)	7,348 (22.4)	
Medicaid	1,206 (3.7)	1,483 (4.5)	
Other	360 (1.1)	324 (1.1)	
Self-pay/uninsured	99 (0.3)	221 (0.4)	
Distance from Hospital			.132[†]
0-5 Miles[‡]	1,284 (3.9)	1,330 (4.1)	
6-10 Miles	2,563 (7.8)	2,759 (8.4)	
11-20 Miles	3,981 (13.2)	4,157 (12.7)	
21-50 Miles	4,344 (13.2)	4,348 (13.2)	
51-100 Miles	1,536 (4.7)	1,593 (4.9)	
101-300 Miles	1,834 (5.6)	1,941 (5.9)	
300+ miles	601 (1.8)	547 (1.7)	
ASA			< .001[†]
ASA 1-2[‡]	8,131 (24.8)	7,853 (23.9	
ASA ≥3	8,012 (24.4)	8,822 (26.9)	
Anesthesia type			< .001[†]
Major/General/Regional[‡]	10,986 (33.5)	11,669 (35.6)	
Monitored anesthesia care (MAC)	3,612 (11)	4,496 (13.7)	
Cardiac anesthesia	1,545 (4.7)	510 (1.6)	
Medication count			< .001[†]
0[3]	1,339 (4.1)	1,413 (4.3)	
1-5	5,494 (16.7)	5,490 (16.7)	
6-10	4,843 (14.8)	4,704 (14.3)	
> 11	4,467 (13.6)	5,068 (15.4)	
Admission status			.972[†]
Outpatient[‡]	3,698 (11.3)	3,838 (11.7)	
Inpatient	11,224 (34.2)	11,575 (35.3)	
Other	1,221 (3.7)	2,483 (7.6)	
Surgical specialty			< .001[†]
Urology[‡]	3,427 (10.4)	3,496 (10.7)	
Cardiovascular	1,615 (4.9)	578 (1.8)	
Colorectal/general	2,340 (7.1)	2,573 (7.8)	
Gynecology	697 (2.1)	723 (2.2)	
Hepatobiliary	791 (2.4)	1,116 (3.4)	
Neurological	1,557 (4.7)	1,776 (5.4)	
Orthopedics	2,694 (8.2)	2,915 (9)	
Otorhinolaryngology	1,673 (5.1)	1,759 (5.4)	
Other	238 (0.7)	285 (0.9)	
Thoracic	701 (2.1)	805 (2.5)	
Vascular	410 (1.2)	649 (2)	

[*] Student *t* test.
[†] $\chi 2$ test.
[‡] Reference category in logistic model.

Table 4
Patient Factors and Odds of Surgical Delay

Patient-specific factor	Odds ratio	95% CI		*P*-value
MAC anesthesia	1.28	1.20	1.36	< .001
ASA ≥3	1.21	1.15	1.28	< .001
African American race	1.25	1.12	1.39	< .001
Renal failure	1.20	1.09	1.32	< .001
Steroid	1.13	1.04	1.23	.004
Medicaid insurance	1.18	1.09	1.30	< .001
Medicare insurance	1.14	1.07	1.21	< .001
Obesity	0.66	0.59	0.75	< .001
Cardiovascular anesthesia	0.36	0.26	0.49	< .001

Table 5
Surgical Specialties and Odds of Surgical Delay

Surgical specialty	Odds ratio	95% CI		*P*-value
Vascular	1.402	1.197	1.642	< .001
Hepatobiliary	1.233	1.105	1.376	< .002
Colorectal/general	1.156	1.068	1.251	< .003
Orthopedic	1.145	1.055	1.242	.001
Otorhinolaryngology	1.132	1.036	1.236	.006
Neurological	1.13	1.033	1.235	.007

findings by Gabriel et al[8], is the difference in samples and settings. The current study was completed in a large, academic hospital that primarily performs complex procedures with a high-acuity patient population and a provider mix that includes trainees. Home medication count was used as a proxy measure of acuity based on the prior validation,[26] but it did not demonstrate a significant relationship with surgical delay in this model. Renal failure increased the odds of delay ($P < .001$), which could be explained by dialysis schedules, venous access challenges, and the need for laboratory testing on surgery day.[27] Finally, steroid use for chronic illness was associated with a surgical delay ($P = .004$). Steroid use has been used as a predictor of morbidity and mortality and may be a useful proxy measure of illness.[28]

One of the few variables that had a decreased odds of being delayed was obesity ($P < .001$). Obesity is often comorbid with other chronic illnesses such as hypertension, heart disease, and diabetes mellitus, indicating a higher disease burden.[29] Additionally, common preparatory practices for the OR such as intravenous catheter placement and blood pressure cuff monitoring can require additional time due to difficulty in patients with obesity.[30,31] Despite higher disease burden in patients with obesity, obesity did not increase the odds of delay in this model, which may be an idiosyncrasy of this sample.

Something that has not been shown in prior studies, but is notable in the present study, is the impact of the type of insurance and race on the incidence of surgical delay. The use of publicly managed insurance, including Medicaid and Medicare, increased the odds of surgical delay ($P < .001$, respectively). Another notable disparity was that African American race increased the odds of surgical delay ($P < .001$). While research among patients with cancer has repeatedly shown treatment delays among minority groups,[32,33] this study is the first known to the authors to find an association between delay and race in the OR setting.

Compared to general anesthesia, cardiovascular anesthesia had a decreased odds of delay ($P < .001$). However, MAC had an increased odds of delay ($P < .001$), consistent with earlier findings in different settings.[8] This may be because MAC cases are usually short with a high case volume, which creates more opportunities for delay. On the other hand, there are usually only 1 or 2 cases requiring cardiovascular anesthesia scheduled in a room on a given day. Furthermore, cardiovascular cases usually have a dedicated team of personnel who regularly work together, are proficient with the equipment, and have a designated room. Dedicated surgical teams have been shown in other surgical populations to improve efficiency with regard to start and turnover times.[34]

The surgical specialty was included in the model due to the highly significant relationship with surgical delay in bivariate analysis ($P < .001$). There were six specialties that had increased odds of surgical delay compared to the reference category, which is likely related to the processes in place at this facility for those surgical

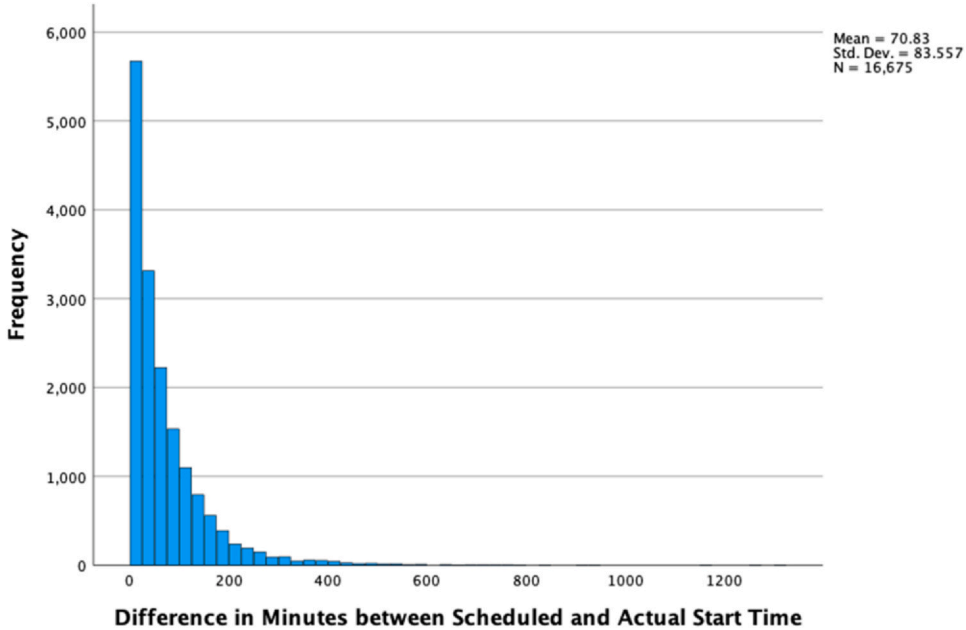

Figure 1. Frequency of late starts by number of minutes since scheduled time. This figure is available in color online at www.jopan.org.

services. It may be helpful in future studies to limit analyses to one surgical service to eliminate bias toward a particular service.

Limitations

Although mandatory EHR adoption provides an enormous volume of electronically accessible patient data for clinical practice and patient outcome measurement, because the information collected has been designed primarily for patient care billing and reimbursement purposes, and reflects individual provider documentation approaches, it is often lacking the needed granularity and standardization for secondary use.[35] This study was similarly met with the challenge of missing data when attempting to gather comorbidity data using ICD-9 codes[18] and ICD-10 codes,[19] which were often missing from the patient's charts. Search terms had to be created to identify comorbidities and home medications; all possible terms for a particular diagnosis or medication may not have been included.

An issue that makes comparing the findings of this study to other studies problematic is that a commonly accepted definition of surgical delay does not exist. In this study, a surgical delay was defined as any start time that was 1 minute past the scheduled time. Other facilities may have a more lenient definition of delay, or allow for a longer grace period, which could change the dynamic and therefore, predictors of delay. In addition, this study looked at all cases throughout the course of the day. It has been shown that second, third, and subsequent cases are more likely to be delayed than the first case of the day due to the domino effect when a prior case is delayed or takes longer than scheduled.[18] This would be especially relevant when considering predictors that might vary throughout the day, such as provider and equipment availability; however, it is presumed that patient factors related to health status would not vary significantly with the time of day.

Due to the retrospective nature of this study, it was not possible to control for the other factors that contribute to surgical delay, as well as quantify their contribution. Data that described other causes of delay such as room or personnel availability or administrative delays were not available. While the model indicates that patient-specific factors make a rather small contribution to surgical delays with a pseudo R-squared of less than 5%, the very large sample size gave this study the power to detect small differences that are statistically, and more importantly, clinically significant. Preventing even one surgical delay is significant to that patient.

This sample represented a primarily older, chronically ill, inpatient population with a large portion of retirees using Medicare. The results of the study cannot be generalized to the whole surgical population, especially when considering ambulatory surgery centers which primarily service outpatient settings and have a large proportion of young, healthy patients. The results are applicable in acute care settings with older, sicker populations, especially since comorbidities are some of the contributing factors to surgical delay. Additionally, the lessons learned from this study would serve future researchers well in designing a study that more accurately identifies the real cause of delay with respect to patients.

Conclusion

Despite many studies on surgical delay, the role of the patient is still not entirely understood. This study confirms that sicker patients with chronic illnesses are more likely to experience a surgical delay using information that was readily available in the EHR. Processes that address these issues proactively, such as preoperative clinics, have been shown to be effective and should continue to be used.[16,17] This study also uncovers evidence of health disparities by race and insurance, which should direct hospital administrators and policymakers to take note of the impact of these factors on the patient experience as well as continue to improve systems and processes related to insurance. Additional studies exploring patient-related surgical delays in other settings such as ambulatory surgical settings, as well as prospective studies that can acquire greater detail regarding characteristics of individuals that may cause a surgical delay, are recommended.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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